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Does value creation skill exist in private equity? A deal-level analysis of private equity value creation mechanisms and their persistence in Europe

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ABSTRACT OF THE
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Previous literature has demonstrated the outperformance of private equity funds over public markets, but the actual causes of outperformance remain unknown. Furthermore, top-quartile funds have found to outperform bottom quartile funds by 7 to 8% annually, but increasing competition and vanishing fund-level persistence has resulted in LPs' inability to find future top-performing funds. However, no studies have so far studied the persistence of different sources and causes of value creation at deal-level, which might reveal the skill of a GP to create persistent value in the future.

In this study, a rarely accessible deal-level dataset was exploited to enable the separation of organic and inorganic value creation. Representing the first study to exploit the IVC 2.0 framework to a large deal-level dataset, the purpose of this thesis was to better understand how value creation over public market comparables is achieved. Furthermore, the persistence of various value creation levers was studied to identify the skill of a GP to create value from a deal to another.

Our results suggest that private equity deals create outperformance mostly by incremental leverage, multiple growth and profitability improvement. Despite the significant revenue growth on average, the majority of it is acquired or attributable to industry growth, leaving little contribution for GP specific skill. On average, multiple growth and incremental leverage are most persistent drivers, while operational improvements seem to be little dependent on GP skill. However, significant differences exist between GPs' value creation patterns, suggesting that various GPs have skills to create persistent value from different sources.

Keywords:	Publishing language:
Private Equity, Value Creation, Persistence, IVC 2.0	English

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Aikaisemmat tutkimukset osoittavat pääomasijoittajien tuottavan julkista markkinaa korkeampaa tuottoa ottamatta kuitenkaan kantaa siihen, miten korkeampi tuotto saavutetaan. Pääomarahastojen tuottojen välillä on merkittäviä eroja, mutta lisääntyvästä kilpailusta ja häviävästä suorituskyvyn jatkuvuudesta johtuen sijoittajat eivät ole onnistuneet löytämään korkeimman tuoton pääomarahastoja. Aikaisemmat tutkimukset eivät kuitenkaan ole tutkineet eri arvonluontiajurien jatkuvuutta, mikä voisi paljastaa pääomasijoittajan kyvyn luoda arvoa myös tulevaisuudessa.

Tässä työssä käytettiin harvinaista transaktiotason dataa orgaanisen ja epäorgaanisen arvonluonnin erottelemiseksi. Soveltamalla ensimmäistä kertaa suurta transaktiodataa IVC 2.0 viitekehykseen, tämän diplomityön tarkoituksena oli luoda parempi ymmärrys siitä, miten julkista markkinaa korkeampi tuotto käytännössä saavutetaan. Työssä tutkittiin myös eri ajurien jatkuvuutta, jolla pyrittiin tunnistamaan pääomasijoittajan kyky luoda arvoa toistuvasti.

Tutkimuksen tulokset osoittavat, että markkinaa korkeampi tuotto luodaan enimmäkseen käyttämällä keskimääräistä markkinaa enemmän velkaa, kasvattamalla käyttökatekerrointa sekä parantamalla kannattavuutta. Vaikka liikevaihdon kasvulla on myös suuri merkitys arvonluonnissa, suurin osa siitä on ostettua tai toimialan kasvun ansiota, ja pääomasijoittajan merkitys jää siksi pieneksi. Käyttökatekertoimen kasvu ja julkisia verrokkeja korkeampi velka ovat myös keskimäärin jatkuvimpia arvonluontiajureita, kun taas operatiivinen kehitys on keskimäärin vähän riippuvaista pääomasijoittajasta. Pääomasijoittajien arvonluontistrategioissa on kuitenkin suuria eroja, ja eri pääomasijoittajilla on kykyjä luoda jatkuvaa arvoa eri arvonluontiajureilla.

Asiasanat: Pääomasijoittaminen, Arvonluonti, Jatkuvuus, IVC 2.0	Julkaisukieli: Englanti

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Helsinki, August 2019

Mikael Kallio

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1. Introduction

1.1 Background

During previous decades, the rapid growth and high performance of the private equity (PE) sector have attracted several academic researchers to investigate the rising phenomenon. Many scholars have argued that the PE ownership model enables PE firms to run portfolio companies in a superior manner, resulting in outperformance over the public market and justifying the high fees of general partners (GPs) (Morris 2014). However, little is known about how GPs create value in their portfolio companies, and especially, whether the outperformance is achieved through incremental leverage, valuation multiple growth or operational improvements in portfolio companies. So far, insufficient value creation frameworks and unavailability of deal-level data prevented scholars from studying value creation with a precision that would answer these questions. Furthermore, some previous studies are based upon data whose reliability has recently been questioned, creating a need for re-evaluating PE performance (Harris et al. 2014b).

In addition to the high performance of the industry, top-quartile PE funds have found to outperform bottom quartile funds by 7 to 8% annually (Korteweg & Sorensen 2017) and generate IRR above 50% (Lopez-de-Silanes et al. 2011). Thus, the measurement of value creation has risen into a key role for limiter partners (LPs) to identify the top-performing funds of the future. However, the increasing competition has caused fund performance persistence to vanish after 2000 (Harris et al. 2014a), causing the failure of LPs to identify future top performers (Sensoy et al. 2014). The lack of persistence at fund-level has raised the need of finding better predictors of future performance (Braun et al. 2017b).

The limitations of fund-level persistence research, such as the overlap of precedent funds, low-frequency data and significant lag of performance information (Braun et al. 2017b), blurs the view of GPs' actual value creation, leaving little investable persistence (Korteweg & Sorensen 2017). Furthermore, fund-level studies fail to identify whether specific GPs have a skill to create persistent value with a particular value creation driver. If such persistent skills emerged, these could be used as better predictors of GPs' future performance, thus offering better chances for LPs to identify top-performing funds, and to foster fund inflows to GPs that truly earn their fees.

1.2 Research objective and questions

The objective of this study is to shed light on the value creation and persistence of private equity investments. By utilizing a rarely accessible deal-level dataset and a sophisticated methodology, we aim to improve understanding of value creation in the private equity industry. By dividing value creation into various sources and causes, we aim to answer the primary research question:

> *How value is generated in private equity investments*?

Since private equity funds have found to outperform public markets gross-of-fees, it is interesting to examine how the GPs create these excess returns. We aim to quantify the abnormal value creation of private equity investments with various drivers to identify how expected outperformance is achieved.

> *How do private equity firms create outperformance over public market comparables*?

After understanding how value is created on average, we aim to study whether historical value creation provides valuable information for LPs when considering future investment opportunities. We aim to quantify the predictive value of historical performance to improve our understanding of the persistence of different value creation drivers.

How persistent is value creation across different value creation drivers?

In addition to understanding the persistence of various value creation drivers in general, we will examine the differences in value creation attribution between GPs. Thus, we aim to understand whether certain GPs can create value at particular value creation levers consistently, indicating a skill that can be turned into value from a deal to another. We will examine the persistence of various value creation drivers, and especially, the ability of GPs to create outperforming value through various sources.

How persistently can specific GPs create value with particular value creation drivers?

1.3 Research design, methodology and scope

1.3.1 Research design and methods

This thesis will consist of theoretical and empirical parts. First, a comprehensive literature review is introduced around the topic to offer a general understanding of the PE sector and especially to summarize the results of previous research in the areas of value creation and performance persistence. While the previous studies do not offer results at the same level of detail as we do, they will provide a solid basis for our study as well as a way to connect our results to the general understanding of PE value creation.

The empirical part of the thesis will be constructed to answer the research questions of the thesis. We will use a deal-level dataset to study the value creation at the level of an individual portfolio company. As far as we know, we will be the first to exploit the IVC 2.0 value creation framework introduced by Zeisberger et al. (2017) as the tool to quantify the value creation of private equity deals. In addition to quantifying the value contribution of particular value creation drivers, their long term persistence will be studied both in general and within specific GPs.

1.3.2 Data sources

Several data sources are needed to gather the necessary information for calculating value creation according to IVC 2.0 framework. Perhaps the most valuable data is the rarely accessible deal-level dataset of private equity transactions. We received the dataset from a fund-of-fund, which used it as a part of a due diligence process to evaluate the GPs' value creation abilities.

Another significant contributor to the results of this thesis was the public company data used to compare each transaction to industry peers. We collected the necessary financial information of public companies from the Capital IQ database. Tax rates were collected from a database of Organisation for Economic Co-operation and Development (OECD). To estimate the cost of debt, monthly LIBOR data was collected from the Macrotrends database. Furthermore, exchange rates were collected from a database of the European Central Bank (ECB).

1.3.3 Scope and limitations

The focus of this thesis will be in buyout (BO) investments and especially leveraged buyouts (LBOs). We will focus on GPs and funds acquiring majority ownerships from target companies, but we will not exclude the exceptional minority investments of these funds. We will focus the discussion of this thesis to buyout investments whenever the results of previous studies can be separated into buyout and venture capital (CV) investments.

Due to the transaction data used in this thesis, and the focus of the fund-of-fund offering the data, this thesis will focus on mid-and large-cap buyout investments in the European region. Thus, we will be one of the first authors to introduce detailed value creation of private equity investments in Europe, while many previous studies have focused either to US or UK.

1.4 Structure

This thesis consists of five chapters. After the introduction of this chapter, a theoretical part will follow introducing the most relevant research around private equity value creation. First, literature review will introduce the concept of private equity asset class to offer a general idea of the operating model including the phases of a buyout fund lifecycle. After understanding the basics, the focus will be on the performance and value creation in buyout funds. First, we introduce the results of fund-level performance studies, and the drivers affecting the performance of a fund. Second, we will shift the focus to value creation at deal-level to understand how value is created according to the previous research. We will introduce the general methods to divide value creation into various levers as well as the sources and causes of value creation. Third, we will introduce the results of previous performance persistence research, which mostly consists of fund-level studies.

Chapter 3 will introduce the data and methods used in this thesis. First, we will introduce the sources of data as well as descriptive statistics for the transaction samples, followed by a discussion of the variables and main assumptions associated with them. We will then introduce the methodology of the IVC 2.0 framework with a comprehensive example calculation. Lastly, we will introduce the methodology for studying the persistence of various value creation levers of the IVC 2.0 framework.

In chapter 4, the results of the analysis are presented. After revealing the average value creation attribution of the samples, the focus will shift towards the variation and persistence of various value creation drivers, both in general and at the level of individual GPs. In the fifth chapter, the practical and theoretical implications of the results are discussed, followed by limitations and suggestions for future research on the topic.

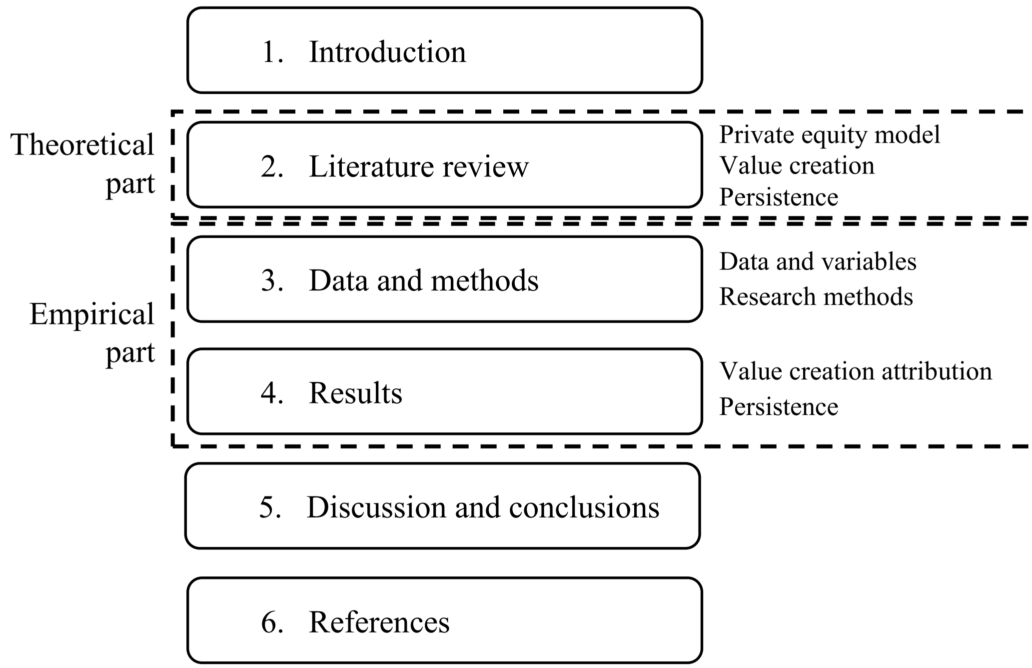


Figure 1 Structure of the thesis

2. Literature review

2.1 Private equity

Private equity (PE) is an asset class investing long term capital into private companies in exchange for an equity stake in the company. Capital is typically raised from institutional investors and invested in several portfolio companies to create value during holding periods. Since the portfolio companies are private and thus their shares can not be publicly traded, PE funds aim to liquidate their investment through various exit routes during the divestment period to realize returns to the investors (Zeisberger et al. 2017).

Institutionally managed private equity can be divided into three main strategies: venture capital (VC), growth equity (GE) and buyouts (BO). Venture capital funds make minority investments in early-stage companies and start-ups, which are often characterized by high risk and high return potential. While most of the target companies are still unprofitable, many also lack revenue or even the first product or service. Growth equity funds invest in more mature businesses that have passed the start-up phase and are typically growing fast. Buyout funds acquire controlling equity stakes in mature companies which are often generating steady cashflows. Majority investments enable restructuring of target companies in the investor's preferred manner to create value in the company. Furthermore, buyouts are often characterized by high leverage and aligned economic interest between a company's management and investing fund (Kaplan & Strömberg 2009, Ljungqvist et al. 2008, Zeisberger et al. 2017). In terms of committed capital, buyout strategy is by far the largest sector, accounting for over 70% of total PE fundraising in Europe in 2017 (Invest Europe 2019).

In addition to the three strategies, private capital – such as investments made by business angels and families – can be seen as an informal part of the private equity field. Furthermore, real assets, such as infrastructure, natural resources and real estate, are traditionally categorized as a subset of PE asset class. (Zeisberger et al. 2017) However, the focus of this thesis will be in buyout funds managed by institutional PE firms, which are further discussed in chapter 2.2.

PE firms are companies specialized in executing one of the previously mentioned strategies. PE firms raise and manage funds through two separate affiliates: general partners (GPs) and investment managers. Most PE funds are closed-end limited partnerships with predetermined lifespan – typically 10 years. Limited partners (LPs) or investors commit their investments for this time period knowing only the mandate of the fund but having no rights towards individual investment decisions. Typical LPs are institutional investors such as insurance companies, banks, pension funds, corporations, family offices and fund of funds (FOFs). (Ljungqvist et al. 2008, Zeisberger et al. 2017) The relationships between a fund's GP, LPs and other stakeholders are shown in figure 2.

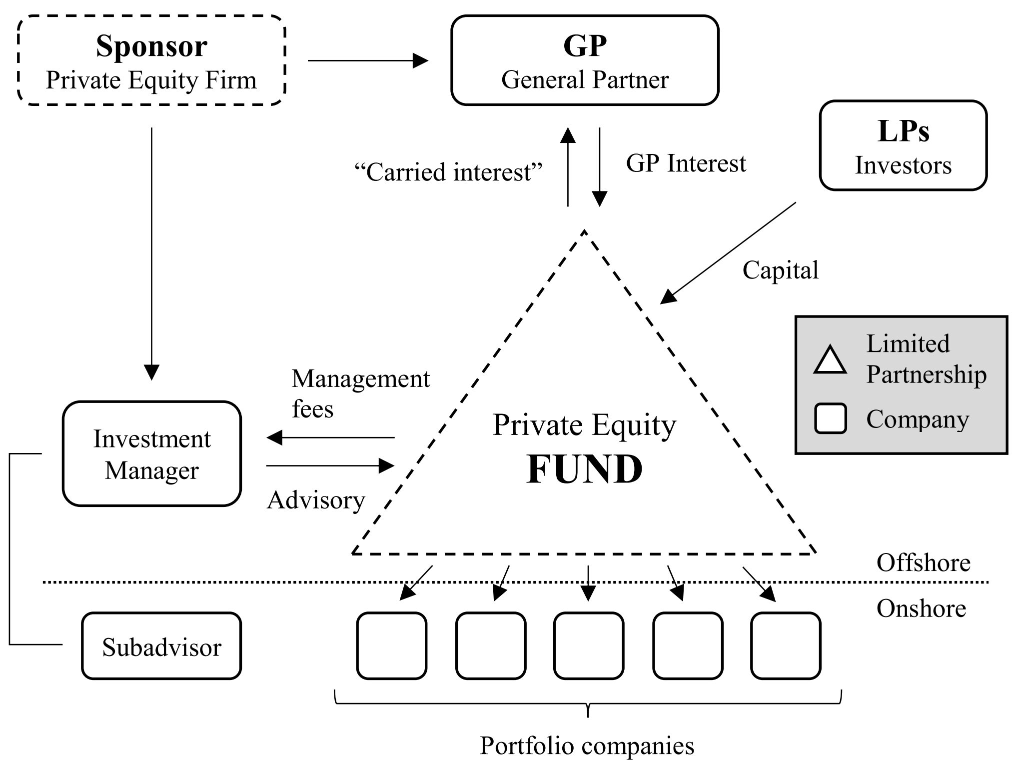


Figure 2 Limited Partnership PE Fund Structure based on Zeisberger et al. (2017)

Figure 2 illustrates the contribution and reward of each stakeholder throughout the lifespan of the fund. GPs are responsible for managing the fund according to investors' interests and they make all investment and divestment decisions to execute the mandate agreed upon with LPs in Limited Partnership Agreement (LPA). While LPs offer the majority of the fund's committed capital, GPs and employees usually also contribute minority shares to align their interests with LPs. (Zeisberger et al. 2017) GPs' contribution is usually at least 1%, while the mean ranges from 5% to 8% and can be as high as 10% of the fund's committed capital (Jacobius 2017, Kaplan & Strömberg 2009, Zeisberger et al. 2017). To foster the alignment of interests between GP and LPs, GPs typically earn 20% of the net profits of the fund, called as the "carried interest" (Kaplan & Strömberg 2009, Zeisberger et al. 2017).

Investment managers are responsible for day-to-day activities of the fund, which include deal sourcing, reporting and advisory services to existing portfolio companies. To cover the expenses of these services and other costs of fund management, investment manager charges an annual management fee of 1 to 2% of committed capital from investors (Kaplan & Strömberg 2009, Zeisberger et al. 2017).

2.2 Buyout funds

PE funds aim to return capital to investors within 10 to 13 years (Harris et al. 2014b, Kaplan & Strömberg 2009), and funds are often raised for "10 + 2" years. Usually, GP has the option for two additional years in cases where more time is needed to exit all investments successfully (Zeisberger et al. 2017). Throughout the lifecycle of a buyout fund, the committed capital is invested in 10-15 portfolio companies on average (Zeisberger et al. 2017). The average lifespans of buyout funds have been increasing from 11.5 years in 2008 to 13.2 in 2014, which might be explained by below expected annual returns and challenging liquidation environment (Bollen 2015).

The lifespan of a PE fund can be divided into four phases: fundraising, investment, holding and divestment period (Zeisberger et al. 2017). Figure 3 illustrates the typical length and timing of each phase in a 10 + 2 year fund. The fundraising period often starts before the first closing and continues for around a year, followed by an investment period of around 5 years. Divestments start around 3 years after the first closing and last until the end of the fund's lifespan. Thus, the holding period lasts from the first closing to the last exit. We will take a closer look at each period in chapters 2.2.1 to 2.2.4.

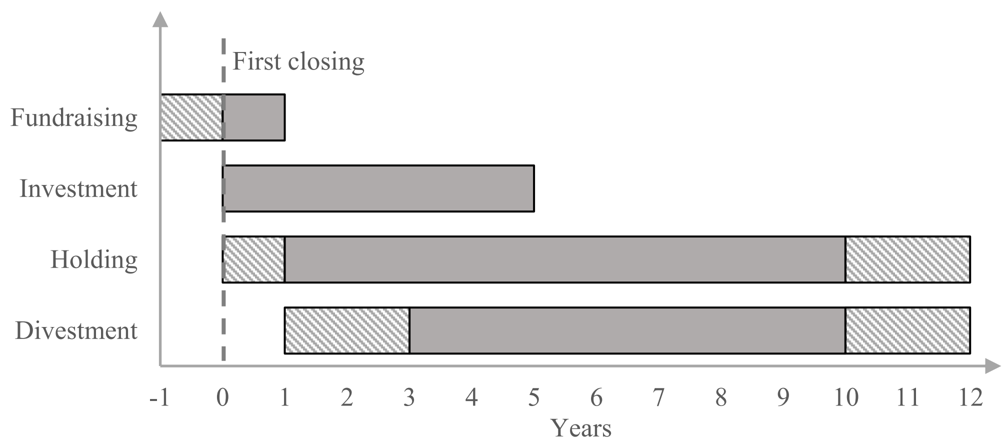


Figure 3 Lifecycle of a buyout fund Based on Zeisberger et al. (2017)

Since the investments are made within several years and parallel to exits from other portfolio companies, the cash flows of a fund formulate a "J-curve" (Aigner et al. 2008). During the first few years, cumulative cash flows are negative due to the acquisitions of portfolio companies. At some point, cash flow from divestments starts to outstrip investments, forming the bottom point for J-curve, which typically equals less than 80% of total committed capital (Zeisberger et al. 2017). When all investments are executed, the remaining cashflows are typically positive, and at some point, cumulative cash flows reach a break-even point, and eventually define the total return of the fund.

Successful PE firms typically raise a fund between every 3 to 5 years (Braun & Schmidt 2014, Chung 2012). In addition to mitigating the risk of poor timing within a fund, raising several funds enables PE firms to invest in necessary resources and use them efficiently in the long term (Zeisberger et al. 2017). Furthermore, as J-curved cash flows of a fund generate most returns and compensation during the latter half of a fund's lifespan, GPs are motivated to raise several funds to generate more stable returns (Braun & Schmidt 2014).

2.2.1 Fundraising period

The establishment of a PE fund begins with an important period of fundraising. For established PE firms, raising a follow-on fund often begins with connecting investors of previous funds (Zeisberger et al. 2017). To convince LPs of the GP's ability to create high returns on investment, the interim performance of previous funds is critical, especially for low reputation GPs (Barber & Yasuda 2017). This motivates GPs to show great performance results early in funds lifespan to get follow-on funding, which can often be seen as successful early exits before follow-on fundraising (Barber & Yasuda 2017). Braun & Schmidt (2014) have shown that deals exited before the final closing of follow-on fund significantly outperform returns of deals exited afterward, indicating the GPs challenge to balance between short and long term motives – getting follow-on funding and generating great returns with the current fund.

For first-time funds, fundraising is often much more difficult due to a lack of GP's comprehensive track record. To earn investors' interest, first-time funds need to create a differentiated investment strategy and an gather experienced team with an adequate implementation plan already before approaching investors (Zeisberger et al. 2017). Specialization to certain geographical area, stage or industry as well as experience may facilitate and speed up fundraising process (Gejadze et al. 2017).

The volume of buyout fundraising has been growing during recent years. Funding raised by direct PE funds focusing on European buyout investments grew from

EUR 34.0 billion in 2015 to EUR 66.5 billion in 2018, after a small decline from the peak of EUR 72.6 billion in 2017. In 2018, buyout fundraising represented 68.3% of total PE fundraising. The relative contribution of investor groups has not changed significantly during previous years, except for pension funds, which have been driving the growth of fundraising as the biggest investor group (37% in 2018). Other large investor groups in 2018 were fund of funds (12%), insurance companies (11%) and sovereign wealth funds (11%). 64.0% of the funding came from European investors, 28.5% from North America and the remaining 7.5% from the rest of the world. In Europe, France was the largest contributor with a share of 10.7% of total fundraising. (Invest Europe 2019)

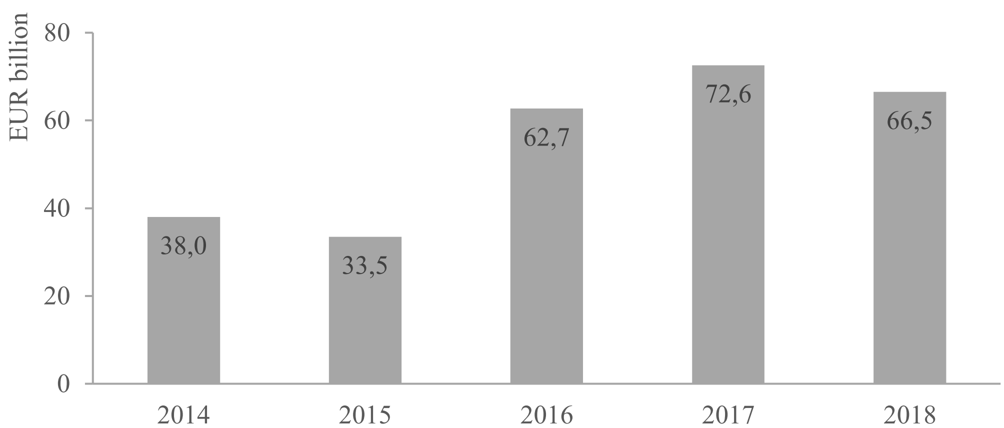


Figure 4 New funds raised (excluding capital gains) by PE focusing on European buyouts (Invest Europe 2019)

2.2.2 Investment period

Once a fund has raised the intended amount of capital, investment period is initiated with the closing of a first deal. During investment period, the raised capital is invested into 10 to 15 portfolio companies on average (Zeisberger et al. 2017). Investment period usually lasts 4 to 6 years (Harris et al. 2014b), while GPs often have an option for 1 to 2-year extension (Zeisberger et al. 2017).

GPs utilize several deal sources to find potential target companies. According to the survey of Teten and Farmer (2010), GPs' professional relationships are primary sources of deal origination in buyout funds and only 44% of deals are sourced through in-house sourcing processes. Word of mouth, cold calls and public statements are also important sources as well as sell-side intermediaries, which represent the source of around a third of deals (Teten & Farmer 2010). These findings are in line with the results of Gompers et al. (2016), who find that around two-thirds of deals are proactively self-generated or generated by an investment bank.

After the identification of a potential target, the sourcing process continues with deep due diligence of the target's business and negotiations with the management of the target company (Zeisberger et al. 2017). According to Teten and Farmer (2010), only one out of 80 reviewed investment opportunities end up to deal closing, while Gompers et al. (2016) conclude that on average, 3.6% of all considered opportunities make it through the entire process.

Buyout targets can also be sourced from different owners and thus be divided based on the type of buyout. Target companies can be publicly listed (public to private), private (independent private), divisions of a larger entity (divisional), owned by another PE firm (secondary), or in a distressed financial situation (distressed) (Zeisberger et al. 2017). Kaplan and Strömberg (2009) collected an extensive sample from Capital IQ consisting of over 17,000 deals between 1970 and 2007 and showed that public to private and divisional buyouts have both accounted for around 30% of deals while independent private and secondary buyouts have both accounted for around 20% during the sample period. Around 1% of buyouts have been distressed buyouts (Kaplan & Strömberg 2009). The share of public to private deals as well as secondary buyouts was, however, growing before the financial crisis in 2008 (Kaplan & Strömberg 2009).

2.2.3 Holding period

Holding period has a central role in the value creation of buyout investments. Buyout investors are typically known as active investors who actively participate with the management teams of target companies. Therefore, alignment of management's and GP's interests is vital and is secured through shared equity ownership. Furthermore, the majority ownership gives GP the right to control the company's decision making through the board of the portfolio company. Majority ownership thus gives GPs of buyout investments an additional opportunity to create value by implementing strategies that best fits their interests (Zeisberger et al. 2017).

From a value creation perspective, holding period represent an increasingly important role (Puche et al. 2015). During holding period, GPs aim to create value through operational improvements in the target company, which are captured through revenue growth, margin improvement and generation of free cash flow (FCF) (Achleitner et al. 2010, Kaserer 2011). Furthermore, especially in buy-and-build strategies, buyout investors often execute add-on acquisitions and aim to create value through the integration of small companies to the platform of the portfolio company (Achleitner et al. 2011).

2.2.4 Divestment period

After holding a portfolio company for around 3–5 years on average, GPs aim to realize the created value by selling the company. The first exit initiates divestment period during which a fund divests all portfolio companies and returns committed capital and profits for LPs. Exits can be done through various routes, and potential exit route is often considered already during due diligence process to evaluate the attractiveness of the target. In general, GPs aim to maximize the exit valuation of the firm and thus choose the exit route that maximizes the returns for funds investors. (Zeisberger et al. 2017)

Kaplan & Strömberg (2009) show that from over 17,000 investments entered between 1970 and 2007, the most common exit route has been a sale to a strategic buyer. Strategic sale is indeed an attractive exit route since industrial buyers often look for synergies, which increase the value of the target, thus increasing the possible sale price and returns for GP (Achleitner et al. 2011). Sale to a financial buyer, such as another PE firm, represents the second most common exit route with a share of 24%. The third most common exit route has been initial public offerings (IPOs), which have accounted for 14% of exits on average but decreased to only 1% of all exits in 2007 (Kaplan & Strömberg 2009). The pricing of IPO exit is highly dependent on public market valuations, and therefore attractiveness of IPO exit – as well as other exit routes – changes significantly over time.

Gompers et al. (2016) studied the intended exit routes of GPs, and the results are quite similar to the results of Kaplan and Strömberg (2009). Sales to a strategic buyer represented the most attractive exit route in their survey, with a share of 51% of responses. Financial sales and IPO represented shares of 30% and 19%, respectively. According to the survey, sales to a strategic buyer have been by far the most profitable exit route, representing an IRR of around 50% on average compared to IRR's of above 30% of other exits (Gompers et al. 2016).

2.3 Buyout fund performance

2.3.1 Performance measurement

GPs and LPs use various performance measures to evaluate the performance of past, ongoing and forthcoming investments. Despite the generally prominent role of discounted cash flow (DCF) and net present value (NPV), only a few investors use those techniques to evaluate investments. Instead, internal rate of return (IRR) and times money (TM) are used almost invariably in PE sector (Gompers et al. 2016).

Perhaps the most widely used measure is IRR, which can be used to measure annualized returns for LPs. In practice, IRR is the rate of return resulting in net present value of zero and can be expressed with the following formula (Kaserer & Diller 2004):

$$\sum_{t=0}^{T} CF_t(1 + IRR)^{-t} = 0\text{, where}$$

T = lifetime of the fund
CF_t = cashflow accrued over period t.

For LPs, IRR indicates annualized returns based on fund contributions and distribution, net of fees and carried interest paid for GP (Harris et al. 2014b). However, before all distributions of a fund are paid to investors, estimations of net asset values (NAVs) of unrealized investments have to be included in IRR calculations (Harris et al. 2014b). Brown et al. (2019) found that unexperienced and underperforming funds tend to manipulate NAVs to overstate past performance and thus to facilitate follow-on funding, while top-performing funds tend to understate valuations of unrealized investments.

Unlike IRR, TM does not take time period into account and thus it measures the absolute returns rather than performance in time. TM – also referred as multiple of invested capital (MOIC) (Gompers et al. 2016) – is usually used as a performance measure of an individual transaction within a fund. Puche et al. (2015) defines TM as follows:

$$TM = \frac{Net\ Capital\ Gain}{Invested\ Capital} = \frac{\Delta\ Equity + Dividends - Capital\ Injections}{Entry\ Equity + Capital\ Injections}.$$

Money multiple (MM) is another widely used measure which is simply calculated as TM + 1 (Achleitner et al. 2010). However, scholars are not unanimous about the definition of these measures, since some measure returns to 100% equity owners and others only for a GP. According to Puche et al. (2015), TM usually reflects returns to 100% equity owners but for example Achleitner et al. (2010) use both TM and MM as a measure of returns to the invested capital of GP. In this thesis, we will follow the definition of Puche et al. (2015) and use TM as the measure of returns to 100% equity owners.

As absolute performance measures, IRR and TM do not take into account the development of public market during the fund's lifetime. To evaluate fund performance in relation to the public market, Kaplan & Scholar (2005) introduced public market equivalent (PME) method, which compares the performance of a fund to a public benchmark, usually S&P 500 Index. Mathematically, PME is defined as follows (Kaserer & Diller 2004):

$$PME = \frac{\sum_{t=1}^{T} cf_t \prod_{i=t+1}^{T}(1 + R_{Ii})}{\prod_{t=1}^{T}(1 + R_{Ii})}, \text{where}$$

R_{Ii} = return of public market index in period *t*
cf_t = normalized positive cash flow (distribution) of the private equity fund in period *t*.

In practice, a PME greater than 1 indicates fund's outperformance over the benchmark index, while PME's smaller than 1 means that the benchmark index has generated higher returns over fund lifetime net-of-fees. Thus, PME expresses how an equally sized investment in the public market index would have performed compared to investment in the underlying PE fund (Kaserer & Diller 2004).

2.3.2 Fund returns

Several researchers have studied the performance of private equity funds to evaluate the profitability of the asset class to its investors. Kaplan and Schoar (2005) used Venture Economics dataset containing 169 buyout funds and found average (median) IRR of 18% (13%) net-of-fees. More recently, Harris et al. (2014b) collected an exhaustive dataset of almost 600 buyout funds from Burgiss database and found median IRR of 14.2%, and median investment multiple of 1.97 net-of-fees.

When compared to the public market, most studies have found buyout funds outperforming benchmark indices. Kaplan and Schoar (2005) conclude that on average, buyout funds' returns roughly equal to S&P 500 returns with PME of 0.97 net-of-fees, while they outperform S&P 500 gross-of-fees. Stucke (2011), however, provided evidence of a lack of updates in Venture Economics cash flow data, which decreased the returns of many funds after the year 2001 in the dataset. Thus, the results of Kaplan and Schoar (2005) have later been questioned, and it is argued that the biased dataset understates the performance of buyout funds (Harris et al. 2014b).

Ljungqvist and Richardson (2003) also used S&P 500 Index as the PME benchmark and found annual excess returns of 6% for PE funds, which they further attributed to illiquidity premium and managers' value creation skills. To control for the conceivable excess risk of PE funds', Ljungqvist and Richardson (2003) calculated betas and risk-adjusted returns and demonstrated that risk-adjusted returns of PE funds still beat public market. More recently, the research of Harris et al. (2014b) suggested annual outperformance of over 3%, and 20% to 27% outperformance over the fund's lifecycle net-of-fees. For buyout funds, they found a PME of 1.16. Consistent with this net-of-fee outperformance, Axelson et al. (2013b) found outperformance of 8%, and Lopez de Silanes et al. (2011) a PME of 1.3 gross-of-fees. The results of these studies thus provide strong evidence of GPs' ability to generate higher returns on average than public markets.

While the outperformance of PE funds over S&P 500 Index returns has been demonstrated repeatedly, some studies have criticized previous research about biased datasets and found PE funds to underperform other benchmarks when taking higher betas into account. Phalippou and Gottschalg (2008) criticize earlier studies about inflated NAVs and biased fund samples. They found that S&P 500 Index outperformed PE funds 3% p.a. net-of-fees and 6% when adjusted for risk. A few years later, Phalippou (2013) argued that PE funds invest in small-cap companies, and thus small-cap index should be used as a benchmark instead of S&P 500 Index. Using French small-value index and DFA's value mutual fund as benchmarks, Phalippou (2013) found average PME's of 0.96 and 1.00 respectively, and PE funds' underperformance of 3.1% p.a. and PME of 0.9 when adjusted for a higher beta. These results indicate how sensitive PME results are to benchmark selection and thus highlight the problems related to PME method when used as an indicator of GPs' ability to create abnormal performance.

2.3.3 Performance drivers

Since the outperformance of private equity funds over public markets seem to be proven – at least gross-of-fees – researchers have shifted the focus towards explaining the abnormal returns of the asset class. Several studies have investigated the drivers of PE fund returns to better understand the sources of the relatively high performance. Based on previous literature, drivers can be broadly divided into two categories: exogenous factors and endogenous factors (Aigner et al. 2008).

Exogenous drivers refer to external factors, such as public market development, interest rate and GDP growth. Researchers have identified several exogenous factors that have been driving the returns of PE funds. Phalippou and Zollo (2005), and Jegadeesh et al. (2009) found a positive correlation between fund performance and gross domestic product (GDP). Also, Aigner et al. (2008) identified positive correlation between GDP with both IRR and PME, and negative correlation between performance and vintage year GDP. Similarly, Phalippou and Zollo (2005), and Aigner et al. (2008) identified stock market returns to be positively correlated with fund performance, and negative correlation between performance and vintage year stock market, using MSCI World Index as the benchmark. Contrary to these findings, Diller and Kaserer (2009) found no correlation between performance and stock market returns and negative correlation between performance and GDP.

Since high leverage is peculiar to buyout transactions, the returns of PE funds are subject to capital and credit market conditions. Phalippou and Zollo (2005), and Aigner et al. (2008) found negative association between fund returns and interest rates, and Robinson and Sensoy (2013) concluded debt market conditions to have a significant impact on PE cash flows. Ljungqvist et al. (2008) also found that lower debt yields were associated with higher returns. Phalippou and Zollo (2005) found positive association between corporate bond yields and fund performance. Aligned with their findings, Jegadeesh et al. (2009) found negative association between credit spread and performance, using the difference between the yields of BAA and AAA-rated corporate bonds. However, Axelson (2013a) found that higher leverage leads to lower returns and justified the claim with the acquirers' tendency to overpay in favourable credit conditions.

Another significant market-related factor driving the performance of PE funds is the increasing competition of target companies, which has led to an increased amount of uninvested committed capital – called the "dry powder" – in the industry (Zeisberger et al. 2017). Gompers and Lerner (2000) introduced this driver as the "money chasing deals" phenomenon and found evidence of industry's total fund inflows driving the valuations of funds' investments, thus affecting the returns of PE funds. While this phenomenon is especially strong in more illiquid and segmented VC funds (Diller & Kaserer 2009), it is also present in buyout funds, of which Ljungqvist et al. (2008) and Harris et al. (2014b) provided evidence. Using a sample of 207 buyout funds, Ljungqvist et al. (2008) found that the greater the inflow of money into private equity funds, the longer it takes for GP to meet LPs' target returns. Furthermore, they concluded that the decreasing number of favourable investment targets leads to lower returns of PE funds, fostering the effect of the phenomenon. Table 1 summarizes the associations between exogenous drivers and fund performance.

Table 1 Findings of exogenous fund performance drivers in previous literature

Driver	*Findings*	*Research*
Stock market return	Association (+)	(Aigner et al. 2008, Phalippou & Zollo 2005)
	Vintage year MSCI return (–)	(Aigner et al. 2008)
GDP	Association (+)	(Aigner et al. 2008, Jegadeesh et al. 2009, Phalippou & Zollo 2005)
	Vintage year GDP (–)	(Aigner et al. 2008)
	Economic development (–)	(Diller & Keserer 2009)
Credit market conditions	Credit spread (–)	(Jegadeesh et al. 2009)
	Corporate bond yields (+)	(Phalippou & Zollo 2005)
	Debt yields (–)	(Ljungqvist et al. 2008)
	Interest rate (–)	(Aigner et al. 2008, Phalippou & Zollo 2005)
Competition	Association (–)	(Diller & Kaserer 2009, Gompers & Lerner 2000, Harris et al. 2014b, Ljungqvist et al. 2008)

Signs in parentheses illustrate positive (+), negative (–) or lack of association (?) between the underlying factor and fund performance.

In addition to exogenous drivers, several endogenous factors have been found to explain PE funds' performance. Endogenous drivers refer to fund characteristics such as size, region and industry. One of the most studied driver is fund size, of which literature provides somewhat contradicting results. Phalippou and Zollo (2005) found positive association between fund size and performance with a dataset containing 539 VC and 166 buyout funds. Kaplan and Schoar (2005) found concave, albeit not significant association between buyout funds size and performance, and positive association for all funds in cross-section. Similarly, Harris et al. (2014b), Kaserer and Diller (2004), and Lopez-de-Silanes et al. (2011) find no relationship between buyout fund size and performance, while a strong positive relationship is present for VC funds (Harris et al. 2014b).

Lopez-de-Silanes et al. (2011) find that the number of simultaneous investments has negative relation to fund performance, which in turn is conflicting with the results of Aigner et al. (2008), which suggest a positive association. Aigner et al. (2008) and Humphery-Jenner (2011) found negative association between fund size and performance, which further illustrates the inconsistent results of the studies. For buyout funds, however, the relation between fund size and performance seems to be rather negative than positive, indicating diseconomies of scale. Marquez et al. (2014) justify the phenomenon as fund managers attempt to keep fund size small to demonstrate value adding abilities for prospective firms and keep the costs of firm development low.

To evaluate GPs' ability to create value, researchers have studied the effect of GP experience to fund performance. Aigner et al. (2008), Diller and Kaserer (2009), and Phalippou and Gottschalg (2008) have shown that the increasing experience of GP results in higher fund performance on average. Similarly, Phalippou and Zollo (2005) found that inexperienced funds perform worse than PE funds on average. While higher experience might be associated with higher management fees, Robinson & Sensoy (2013) show positive association between fees and performance, indicating that experienced managers can justify higher fees. Despite the higher performance of experienced GPs, Aigner et al. (2008) found experienced GPs to make more unprofitable investments, which indicates their higher appetite for risk. Idiosyncratic risk is another driver that has been found to be positively associated with fund returns (Diller & Kaserer 2009, Ljungqvist & Richardson 2003, Phalippou & Zollo 2005). Table 1 summarizes the associations between endogenous drivers and fund performance.

Table 2 Findings of endogenous fund performance drivers in previous literature

Driver	*Findings*	*Research*
Fund size	Association (+)	(Higson & Stucke 2012, Kaplan & Schoar 2005, Phalippou & Zollo 2005)
	Association (–)	(Aigner et al. 2008, Humphery-Jenner 2011)
	Association, buyout funds only (?)	(Harris et al. 2014b, Kaplan & Schoar, 2005, Kaserer & Diller 2004, Lopez-de-Silanes et al. 2011)
Number of simultaneous investments	Association (+)	(Aigner et al. 2008)
	Association (–)	(Lopez-de-Silanes et al. 2011)
GP	GP experience (+)	(Aigner et al. 2008, Diller & Kaserer 2009, Korteweg & Sorensen 2017, Phalippou & Gottschalg 2008)
	Management fees (+)	(Robinson & Sensoy 2013)
Idiosyncratic risk	Association (+)	(Diller & Kaserer 2009, Ljungqvist & Richardson 2003, Phalippou & Zollo 2005)
	Beta (?)	(Phalippou & Zollo 2005)

Signs in parentheses illustrate positive (+), negative (–) or lack of association (?) between the underlying factor and fund performance.

Several researchers have aimed to explain the performance of PE funds with different exogenous and endogenous drivers. Despite the large number of studies, strong evidence remains to be provided to explain whether the superior performance is due to the experience of GP or pure luck (Gohil & Vyas 2016). To better understand the sources of abnormal returns, researchers have shifted their focus towards value creation at deal-level.

2.4 Deal-level value creation

2.4.1 Value creation decomposition

To understand the performance of PE funds and how they perform compared public markets, one must understand how value is being created at deal-level (Harris et al. 2014b, Puche et al. 2015). Berg and Gottschalg (2005) introduce three alternative approaches to deal value creation. First, created value can be divided based on the phases it is being created. These phases refer to the four periods of fund lifecycle introduced in chapter 2.2. Second, value creation can be divided based on the source of value creation – intrinsic or extrinsic – depending on the degree to which it depends on equity investor's activity. Intrinsic value creation refers to value creation that would have emerged without the contribution of equity investor, whereas extrinsic value creation is inherently linked to equity investor's characteristics, such as network, experience, expertise or other capabilities. Third, perhaps most commonly, value is divided based on its causes. Following simple accounting math, equity value can be decomposed into four components, leading to the following formula (Berg & Gottschalg 2005):

$$\textit{Equity value} = \textit{Valuation multiple} * \textit{Revenue} * \textit{Margin} - \textit{Net debt.}$$

Changes in equity value can thus be linked to one of the four components. The change in equity value is commonly captured with a methodology called value bridge, which resembles the previously presented formula. Conventional value bridge captures the contribution of changes in valuation multiple, EBITDA and net debt to change in equity value of a company, using TM as the unit of value creation (Zeisberger et al. 2016). While the method is highly simplified, it is easy to apply and thus widely used among industry practitioners (Achleitner et al. 2010, Porter & Porter 2018).

On the other hand, the conventional value bridge has several severe limitations. For example, it does not take into account the capital structure of a company, which precludes the comparison of investments with unequal financial risks (Achleitner et al. 2010, Porter & Porter 2018). Furthermore, multiplication of simultaneous changes in EBITDA and valuation multiple causes a combination effect that is commonly allocated to multiple driver, overstating its contribution to total value creation (Achleitner et al. 2010, Puche et al. 2015, Zeisberger et al. 2016). These limitations have motivated scholars to develop advanced frameworks.

The risk of a leveraged company consists of operational and financial risk and is thus subject to debt-to-equity ratio. Achleitner et al. (2010) took this fact into account and divided changes in equity to return generated by 100% equity financed company and leverage effect using the following unlevering formula:

$$r_{u,i} = \frac{r_{l,i} + r_{D,i}\left(\frac{D}{E_i}\right)}{1 + \left(\frac{D}{E_i}\right)}, \text{where}$$

$r_{u,i} =$ unlevered return

$r_{l,i}$ = levered return

$\frac{D}{E_i}$ = average debt-to-equity ratio

$r_{D,i}$ = average cost of debt.

Achleitner et al. (2010) added another component to unlevered value creation by including combination effect resulting from the multiplication of simultaneous changes in EBITDA and multiple. Furthermore, they replaced net debt component with FCF effect, which represents the free cash flow generated to pay off debt and finance dividends, thus eliminating some limitations of the conventional value bridge. Kaserer (2011) and Puche et al. (2015) further developed the value bridge of Achleitner et al. (2010) by dividing EBITDA effect into margin and revenue components. As in the case of multiplication of changes in valuation multiple and EBITDA, they added a combination effect component resulting from the multiplication of simultaneous changes in margin and revenue. The resulting framework is illustrated below with a fictional transaction.

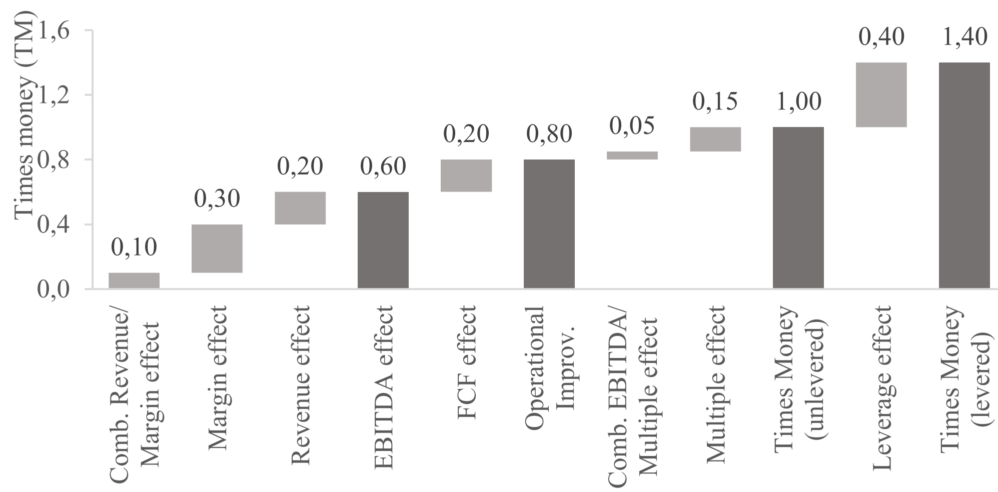


Figure 5 Advanced value bridge introduced by Puche et al. (2015)

Although the advanced value bridge offers significantly more transparent picture of transaction value creation across different levers, it still has significant shortcomings. The framework does not separate intrinsic and extrinsic value creation and thus fails to indicate whether the value creation was achieved by favourable market conditions or GP's actions and skills (Porter & Porter 2018). Furthermore, especially in buy-and-build strategies, add-on acquisitions represent a significant part in value creation, but the methodology fails to distinguish whether the value creation was achieved through organic or inorganic activities. Thus, the framework does not elicit abnormal performance of GP, and can not be used to evaluate and understand GPs ability to create value (Zeisberger et al. 2016)

To overcome these limitations, Zeisberger et al. (2016) introduced IVC 2.0 framework. In addition to the value creation levers introduced by Puche et al. (2015), IVC 2.0 framework divides value creation components into sub-components representing value creation through acquisitions and public market development, revealing the components of GPs abnormal performance. To the best of our knowledge, no studies have so far applied this framework with large deal-level dataset. In this thesis, we will apply this methodology, and introduce it in detail in chapter 3.3.2.

2.4.2 Deal characteristics and returns

The most extensive studies have shown buyout deals median IRRs to range from 20 to 21%, and PMEs to range from 1.29 to 1.3 (Braun & Schmidt 2014, Lopez-de-Silanes et al. 2011, Puche et al. 2015), while TMs have been around 2.4 (Kaserer 2011, Puche et al. 2015). These findings are in line with GPs' target IRR of 20 to 25% introduced by Gompers et al. (2016). Studies with smaller and more niche samples, however, have reported median IRRs over 40% (Acharya et al. 2012, Kaserer 2011). To better understand the variation in deal-level returns, scholars have divided samples based on their characteristics and have found interesting results.

Table 3 Most extensive performance studies conducted with deal-level data

Research	*Sample size*	*Regions*	*Period*
Lopez-de-Silanes et al. 2011	7,453	Worldwide	1973–2005
Graf et al. 2012	12,096	Worldwide	1973–2008
Braun & Schmidt 2014	10,566	Worldwide	1976–2007
Puche et al. 2015	2,029	Worldwide	1984–2013

As a consequence of the maturing industry, the returns of investments have been declining significantly. Lopez-de-Silanes et al. (2011) found median IRRs declining from 26% between years 1973 and 1995 to 18% between 1996 and 2005. The relatively high-performing final sample of Puche et al. (2015) indicated 51% IRR for investments exited before 2000 compared to the IRR of 25% of investments exited between 2009 and 2013, thus providing rare evidence of post-financial crisis returns. In addition to declining trend, Graf et al. (2012) provided evidence of cyclicality of the returns. Deals exited during the dot-com bubble (1998-2001) and buyout bubble (2005-2007) yielded significantly lower returns compared to others due to challenging exit environments.

Size of a transaction – usually measured as the equity investment size – has been found to be positively associated with deal returns (Nikoskelainen & Wright 2007, Söffge & Braun 2018, Valkama et al. 2013). Assuming that investment size is associated with fund size, the result indicates a conflict with the fund-level literature indicating rather diseconomies of scale (Aigner et al. 2008, Humphery-Jenner 2011). Nikoskelainen and Wright (2007) justify the outperformance of large investment with lower bankruptcy risk, diversified business portfolios and PE sponsors increased motive to support large equity investments. The scholars, however, are not unanimous about the outperformance of large investments. Lopez-de-Silanes et al. (2011) found large investments outperforming small when compared to industry benchmark, but similar returns for all investment sizes using absolute performance measures. These findings, in turn, are conflicting with the sample of Puche et al. (2015), who find negative correlation with absolute performance measures. Related to equity investment size, Aigner et al. (2008) and Kaserer (2011) found positive association between buyout ratio and deal returns.

Regardless of the performance measure, Lopez-de-Silanes et al. (2011) found significant negative relationship between the length of holding period and returns of the investments. The median TM multiples ranged from 2.4 of under 2-year investments to 1.6 of over 6-year investments, and the difference was even greater with PME and IRR measures. Related to intra-fund timing, Braun and Schmidt (2014) found deals exited before the closing of follow-on fund to significantly outperform deals exited afterward, which indicates GPs' motive to prove high performance for LPs to facilitate follow-on fundraising.

Deal returns are also dependent on exit method, which explains some of the variation among investments' returns. Lopez-de-Silanes (2011), Kaserer (2011), and Nikoskelainen and Wright (2007) found IPOs to create the highest IRR, while SBOs yielded the highest TM in Kaserer's research (2011). The high performance of SBOs is supported by the results of Achleitner and Figge (2014) who find secondary buyouts to be 6 to 9% more expensive for buyers than other buyouts, indicating higher exit price for selling party. Furthermore, Nikoskelainen and Wright (2007) (2014)found management equity stake to be significant return driver in large and successful buyouts, and Guo et al. (2011) found those buyouts to perform better where CEO is replaced. These results indicate the importance of aligned interests and management's capabilities.

To the best of our knowledge, Puche et al. (2015) are the only ones who have studied and compared deal value creation attribution in different geographical areas with a large dataset. They found North American deals to generate higher returns than European and Asian deals, with TM of 3.8 compared to 3.3 in the rest of the world. The closer examination of return drivers revealed that higher returns were mostly explained by higher leverage of North American deals.

The most comprehensive analysis of deal returns across different industries was conducted by Graf et al. (2012), who divided returns into abnormal and industry returns. Of 3,296 international buyout transactions, natural resources, high-tech & semiconductor industries yielded the highest returns with average IRRs of 70.6%, 62.1% and 59.1%, respectively. In contrast, leisure, consumer industry and industrials & manufacturing industries yielded the lowest returns, with average IRRs of 7.8%, 29.1% and 32.8%, respectively. Puche et al. (2015) studied value creation across industries using conventional value bridge. By dividing transactions to industrials, consumer services, consumer goods and technology services industries, they found TMs of 3.7, 3.6, 3.3 and 2.8, respectively, with only minor relative differences in value creation drivers.

2.4.3 Causes of value creation

As shown in the previous chapter, deal returns vary depending on several factors, including deal size, buyout ratio, industry, geographical area and exit methods. Therefore, to better understand how value is created at deal-level, scholars have taken a closer look at the causes of value creation. As in the advanced value bridge of Puche et al. (2015), value creation can be split into three main categories: operational improvements, multiple expansion and leverage (Kaplan & Strömberg 2009).

As a consequence of increasing competition and tightened credit conditions, the role of operational improvements in value creation has been growing. Puche et al. (2015) find that operational improvements account for around 50% of value creation since GPs have been forced to go deeper into portfolio companies to find value creation opportunities. In the sample of Kaserer (2011), operational improvements played an even greater role accounting for around 75% of value creation. These findings are in line with the results of Graf et al. (2012) and Gompers et al. (2016) who conclude operational improvements to be the main driver of value creation.

Despite the small number of studies examining the value creation among operational improvement drivers, revenue growth seems to be the main driver over margin growth and FCF effect. Kaserer (2011) found revenue growth to account for around half of the value created through operational improvements and around 40% of total value creation. Puche et al. (2015) found similar results concluding that revenue growth accounted for 60% of the value created through operational improvements and 30% of total value creation on average. Puche et al. (2015) also found revenue growth to be a significant value driver, especially for small companies. Söffge and Braun (2018) differentiated organic and inorganic deals and found revenue growth to be a significant value driver only for organic deals, which illustrates the various value creation opportunities offered by different strategies. Margin improvement and FCF seems to be less significant causes of value creation in buyouts. Both Puche et al. (2015) and Kaserer (2011), however, found FCF to be a more significant driver than margin growth. Kaserer (2011) found FCF to account for 27% of value creation while the contribution in the sample of Puche et al. (2015) was 12%. The corresponding values for margin effect were only 17% and 7%. The trend in FCF contribution has, however, been declining while the margin effect has remained approximately the same during previous decades (Puche et al. 2015).

The second category for value creation is multiple expansion, which is driven by two main factors: market timing skills and negotiation skills of the PE firm (Achleitner et al. 2011). Interestingly, previous studies have found multiple growth to have a rather small contribution to value creation. Puche et al. (2015) found a contribution of 15% while Guo et al. (2011) found multiple to account for around 20% of returns to pre-buyout capital. Puche et al. (2015) also found that multiple expansion was more important driver for small companies, which might be explained by the lower valuation multiples of companies with higher bankruptcy risk. Kaserer (2011), however, found that portfolio firms were sold at lower multiples than acquired, resulting in a contribution of -10% to value creation.

The third category of value creation is the leverage effect resulting from debt used in acquisition financing. Achleitner et al. (2010), Kaserer (2011) and Puche et al. (2015) all found leverage effect to contribute around a third of value creation. However, Axelson et al. (2013a) and Braun et al. (2017a) found higher leverage to be associated with lower returns, which is explained by acquirers' tendency to overpay when access to credit is easier. However, the contribution of leverage has been decreasing as a consequence of tightening credit market conditions. Puche et al. (2015) found a decline from 34% in deals exited between 1987 and 2000 to 30%

in deals exited between 2009 and 2013. They also illustrated significant positive association between relative leverage contribution and deal size. Valkama et al. (2013) found that leverage barely improved value creation in buyouts but did inflate equity returns, especially in high performing deals.

Although the contribution of the three main categories can be separately observed, the categories are not mutually independent. Achleitner et al. (2011) found a positive association between sales growth and exit multiples, thus offering a third alternative path for multiple expansion. They justified the association by acquirers' willingness to pay a premium for sustainable past growth and the correlation of increased sales with more stable cash flows (Achleitner et al. 2011). Similar association was not found for margin and exit multiple (Achleitner et al. 2011) or EBITDA and leverage (Kaserer 2011). However, previous research shows that in addition to direct impact, value drivers may have indirect effects on value creation through the influence on other drivers.

2.4.4 Sources of value creation

The sources of value is the second approach to value creation introduced by Berg and Gottschalg (2005). The source of value creation can be either intrinsic or extrinsic, depending on the degree to which it depends on equity investor’s activity. Intrinsic value creation refers to value creation that would have emerged without the contribution of equity investor, whereas extrinsic value creation is inherently linked to equity investor’s characteristics, such as network, experience, expertise or other capabilities (Berg & Gottschalg 2005). Extrinsic value creation is often referred as abnormal performance or alpha whereas intrinsic value creation is captured trough market development driver using index or peer group as a benchmark.

Researchers have aimed to separate intrinsic and extrinsic value creation by comparing investment returns to various benchmarks. Graf et al. (2012) used an extensive sample of over 3,000 buyout transactions and found that alpha represented 76% of value creation, while public market development represented the remaining 24%. While most fund-level studies use S&P 500 Index as the PME benchmark, Graf et al. (2012) used worldwide total return indices of 12 industries to compare each investment to the development of the corresponding industry. Acharya et al. (2012) separate the effect of leverage from the returns and find leverage accounting for 50% of value creation while alpha and public markets contributed 34% and 16%, respectively. The results of the studies are summarized in figure 6.

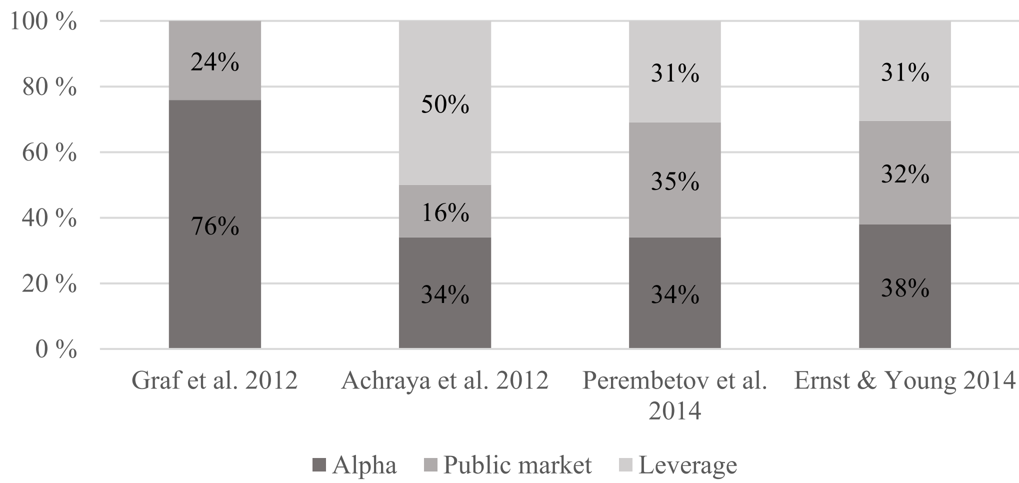


Figure 6 Results of value creation through alpha, public market and leverage

Perembetov et al. (2014) conducted another research using a sample of 241 buyouts. They found leverage effect to account for only 31% of created value, while public market development contributed 32%, leaving the remaining 38% to alpha. Ernst & Young (2014) found alpha to contribute 38% of value on average while public markets accounted for 32% of created value. The results of Perembetov et al. 2014, however, are not comparable with the studies of Acharya et al. 2012 and Ernst & Young 2014, who calculate leverage as the additional leverage compared to public peer group companies. Ernst & Young (2014) find additional leverage to account for 31% of value creation. Although the returns have been declining during the period of the sample of Ernst & Young (2014), they find that the relative contribution of alpha has increased from 34% between 2005 and 2007 to 41% between 2010 and 2013. During the same time period, the contribution of leverage has declined from 33% to 26% while the contribution of public market has remained roughly the same.

2.5 Performance persistence

When considering investment opportunities, pension funds, funds-of-funds and other LPs use past investment performance to evaluate a GP's ability to create value in the future. While high past performance indicates a GP's value creation ability in the past, it is a good predictor of future performance only if the performance of the GP is persistent. To address LPs' issue of finding top-performing PE funds, scholars have conducted researches to study the persistence of PE funds' performance.

One of the pioneering works in this field was the study of Kaplan and Scholar (2005), who were the first to provide evidence of performance persistence. They used a sample of 169 buyout funds of vintages between 1983 and 1997 and found strong persistence across both ends of performance distribution with both IRR and PME measures. They also checked that the results are not driven by differences in risks, industry, investment stage or sample selection bias.

Several other scholars later confirmed the results of Kaplan and Scholar (2005). Aigner et al. (2008) studied persistence by comparing the quartiles of two consecutive funds of a GP, i.e. Markov transition probabilities. They used net and gross IRR and PME measures and demonstrated strong persistence in top-quartile using net IRR measure: 42% of top-quartile funds were able to achieve top-quartile performance in the following fund. Also, they found second quartile funds to make higher-risk investments as the probability of achieving top quartile (bottom quartile) performance was 50% (25%). Furthermore, by using several performance measures, Aigner et al. (2008) note that too many funds might claim to be top quartile, since the decision of the used measure is left to fund manager's choice. Harris et al. (2012) later provided a more profound discussion around this issue.

Diller & Kaserer (2009) also found significant persistence for buyout funds: an increase of 1 percentage point in the IRR of the preceding fund led to an increase of 0.4 to 0.7 percentage point in the IRR of the following fund. Contrary to common belief, they conclude that persistence was not achieved through GP's market timing skills. In addition to studying the correlation of two consecutive funds, Chung (2012) studied the persistence to second and third follow-on funds and concluded that performance exists only in the short-term. Furthermore, he states a theory that LPs are chasing top-performing funds, leading to the growth of these funds, incapability to maintain high performance, and eventually to decreasing persistence.

More recent studies have evidenced performance persistence to decrease after 2000. Harris et al. (2014a) found strong persistence for buyout funds before 2000 but persistence only for the lower part of performance distribution post-2000. In other words, they concluded that persistence has disappeared among top-performing funds after 2000. Korteweg and Sorensen (2017) also conclude that performance persistence has decreased post-2000, but they still find substantial persistence both before and after 2000. Buchner et al. (2016) are one of the firsts to study persistence outside the US. They use an extensive deal-level sample and find persistence to exist, and to be weaker outside the US. However, the results are conflicting with the findings of Korteweg and Sorensen (2017) who find stronger persistence outside the US. Buchner et al. (2016) also find that risk is an important driver of performance persistence and is itself persistent.

Korteweg and Sorensen (2017) apply an analysis of variance (ANOVA) method instead of AR(1) models and Markov transition probabilities applied by previous scholars. They isolate three components of persistence: long-term, investable and spurious persistence. The three components illustrate PE funds' ability to create consistently outperforming returns, LPs difficulty of identifying top performers with higher expected returns, and the persistence that arises from the partially overlapping consecutive funds of a PE firm, respectively. By separating the three components of persistence, Korteweg and Sorensen (2017) evidence strong long-term persistence in expected net-of-fee returns and find top-quartile PE firms to have 7 to 8 percentage points higher expected annual return when compared to bottom quartile. Also, they find that more persistence and investable persistence exists among smaller funds. However, due to noisy persistence, they find that identifying future top-performing funds is difficult, leaving little investable persistence. The results are in line with the findings of Sensoy et al. (2014) who find that no particular type of LP can choose outperforming buyout funds.

There are several problems related to studying persistence at fund-level, which might explain the scholars' incapability of finding persistence post-2000. Since follow-on funds are raised typically between 3 to 5 years, and funds lifespan is over 13 years on average (Bollen 2015), consecutive funds have an overlap of around 8 to 10 years on average. Similar economic conditions during two funds thus cause a significant correlation between the returns of the funds, which causes artificial persistence (Chung 2012, Korteweg & Sorensen 2017). Furthermore, two consecutive funds of GP share one investment on average, which fosters artificial persistence (Braun et al. 2017b). Fund-level performance data is usually available net-of-fees which further blurs the view of GPs' real value creation abilities. Thus, fund-level studies focus on persistence between two legal entities – PE funds – rather than gross-of-fees performance of GPs (Braun et al. 2017b).

Having fund-level data also limits significantly the number of consecutive data points available (Korteweg & Sorensen 2017). Most recent funds often include

unrealized investments, which NAV's are often biased and manipulated (Brown et al. 2019), making persistence results less reliable. Realized returns are known only several years after raising a follow-on fund, and therefore can not be used to predict follow-on performance in practice. If unrealized investments are excluded, sample size often decreases significantly, excluding the results of most recent funds.
Some issues of fund-level persistence are caused by the idea of PME – comparing returns to public market index, usually S&P 500. It could be argued that the method is too simplified to identify persistence and GP skills across all geographical areas and industries. Furthermore, when calculating PME, fund-level studies rely on fund vintage year and lifetime and assume that investments are distributed evenly across funds lifecycle. This, however, is not the case in practice, and the distribution of investments across a fund's lifecycle can vary significantly among funds. Thus, changing market conditions during funds lifecycle foster the bias of the PME method and fund-level persistence research (Braun et al. 2017b).

To overcome some of the problems related to fund-level persistence, Braun et al. (2017b) used a deal-level dataset to examine the persistence between two consecutive transactions of a GP using PME as the measure. They find that an increase of 1% in the return of the previous deal is associated with an increase of 10.2 basis points higher return. After controlling for deal and fund characteristics, the number decreases to 6.3 basis points but remains significant. In addition to studying the correlation between two consecutive transactions, they also test if GPs vary systematically in their average performance over all samples and find the identity of GP to explain the heterogeneity across deals to some extent. Consistent with the results at fund-level, Braun et al. (2017b) find that persistence has declined post-2000. The decreasing persistence is partly explained by the increasing competition since they find that significantly higher persistence at times of low competition.

Similarly to fund-level studies, Braun et al. (2017b) also study the performance by quartile and in low and high competition states. They find that top-quartile persistence is high during low competition states but decreases significantly when the competition is high. Furthermore, they find significant bottom-quartile persistence irrespective of the competitive situation. This implies that selecting GPs who perform top quartile deals has become difficult while bottom quartile performers could still be avoided to some extent.

2.6 Synthesis of literature review

Several scholars have studied the performance of PE funds as well as the underlying drivers. Exogenous drivers, such as stock market returns, GDP, credit market conditions, and competition, as well as endogenous drivers, including fund size, fund vintage, GP experience, number of portfolio companies, and idiosyncratic risk have been found to explain the variation in PE returns. Most studies have found PE funds to outperform public markets – at least gross-of-fees – indicating that PE firms are able to grow companies faster than public markets on average.

To understand how outperformance is achieved, scholars have studied value creation at deal-level. In addition to fund-level drivers, transaction size, holding period, exit method, geographical area, and industry have been found to be significant performance drivers at deal-level. The scholars studying the causes of value creation have found operational improvements to have an increasingly important role in value creation while the leverage effect has decreased slightly over time. Operational improvements are mainly achieved through increasing sales which indicates GPs increasing need to dig deeper into portfolio companies' businesses to find value creation opportunities.

Other scholars have approached value creation from the perspective of causes. Depending on the method applied, some scholars have found leverage, market returns and alpha to have a roughly equally important role in value creation while others have found alpha to have even greater role. Previous scholars have, however, used oversimplified benchmarks to extract alpha, which often does not take industry or geographical area into account. Furthermore, their methodologies have not been able to reveal whether the value creation was achieved through organic or inorganic growth, which adds serious bias to the results of these studies. No studies have so far combined the view of value creation sources and causes, or explained how PE deals create the outperformance over public markets in detail.

LPs are looking for high returns and thus aim to identify future top-performing funds. LPs utilize the information of GPs' previous performance to evaluate whether they should invest in the follow-on funds. However, the process is reasonable only if GPs can create value persistently, meaning that previous performance is a good predictor of future performance. Scholars have studied persistence mostly at fund-level and found significant persistence pre-2000. Post-2000, however, persistence has decreased significantly due to increasing competition, leaving little investable persistence.

3. Data and methods

3.1 Data

3.1.1 Data collection

The rarely accessible PE transaction data was collected from a fund of fund (FOF) investing in the funds of other PE firms. The focus of the FOF is in managers investing in small- and mid-cap companies in Europe, and thus the dataset and this thesis are focused on the value creation of these segments. The transaction data was collected from European PE managers as part of the due diligence process of the FOF to evaluate the past performance of PE firms. The entire dataset contained a total of 1,685 transactions executed between 1989 and 2018.

The dataset contained information about PE firms, fund characteristics, fund cash flows for each investment as well as entry, exit and acquired financials for all transactions. Most transactions of the dataset, however, were not realized or missed one or more datapoint needed in the calculations, and thus could not be used in the analysis. Table 4 illustrates the process of formulating final samples by excluding insufficient transactions.

Table 4 Sample selection process

Sample name	*Excluded transactions*	*N*	*IRR*	*TM*
Entire dataset		1'685	*N/A*	*N/A*
	Transactions with missing information to calculate IRR and TM			
		713	43.0%	3.2
	Unrealized investments			
		332	52.7%	3.9
	Insufficient input values, missing industry peers			
Full sample		297	52.5%	3.2
	No add-on data			
Add-on sample		75	42.3%	2.6

First, transactions with missing values to calculate IRR and TM values were excluded, resulting in 713 transactions with an average IRR of 43.0% and average TM of 3.2 for 100% equity owners. Second, transactions for which realized value was below 75% of total estimated value were excluded to mitigate the bias caused by NAV's of unrealized investments and to better capture the effect of private equity owner on value creation. This resulted in a sample of 332 transactions with an average IRR of 52.7% and an average TM of 3.9. Value creation attribution was calculated for this sample, but results were drawn only for 297 transactions due to failure to find enough comparable public companies for some transactions. Furthermore, insufficient input values caused calculation errors in the case of some transactions, and therefore those were excluded in the calculations. The average IRR of the resulting sample (full sample) was 52.5% while the average TM was 3.2.

The data of the full sample has a shortcoming which affects the reliability of the value creation results. Of 297 transactions, 222 transactions lacked add-on data and therefore acquired value could not be separated from organic value creation in all transactions. Furthermore, it was not reported whether additional equity injections were executed in these 222 transactions, and thus the actual return on equity might have been lower. For this reason, we limited the dataset to 75 transactions (add-on sample) which contained full add-on data or information that no add-ons were executed. As expected, capital injections of add-on sample lowered average IRR to 42.3% and average TM to 2.6. In general, both samples seem to represent well the entire sample when it comes to the returns on equity. In further analysis, we will use both samples to have both a large sample size and accurate value creation data. Detailed descriptive statistics of both samples will be presented in the next chapter.

While most previous studies use S&P 500 as the benchmark investments, we used a set of comparable public companies with several financial measures to extract the abnormal performance of GPs. The financial information of public companies was collected from Capital IQ database using geographical area, SIC-codes, company type and dates as selection criteria. The final sample contained financial information of 8,761 public companies between years 1990 and 2019.

Interest rates were needed to quantify the total impact of incremental leverage on value creation. While Achleitner et al. (2010) used a fixed base rate for all transactions, we calculated individual interest rates for each transaction. Following Puche et al. (2015), we used LIBOR of entry month as the base rate for each transaction. Furthermore, we added 300 basis points – median spread over LIBOR of LBOs between 1993 and 2005 reported by Ivashina and Kovner (2011) – to get the total interest rate for each transaction.

Since tax rates were not included in the PE transaction data, corporate tax rates by country were collected to extract the influence of incremental tax shield in value creation. Corporate tax rates were collected from the Organisation for Economic Co-operation and Development (OECD) database, which included tax rates for European countries from year 2000. Following Acharya et al. (2012), we used average corporate tax rate during the holding period in the country of portfolio company's headquarters. Since tax rates before 2000 were not available, tax rates of year 2000 were used for the years before 2000 when calculating average tax rate during holding period for the few investments entered in the '90s. If the tax rate was not available for other reason, we used a fixed tax rate of 35%, following Phalippou & Zollo (2005).

Exchange rates were collected to convert PE transaction data that was reported in various currencies. Using a common base rate for all transactions enabled us to remove the effect of exchange rates on value creation of PE transactions. We used the euro as the base rate which was a natural choice for European transaction data. Furthermore, we used historical exchange rates to convert other currencies to euros. Historical exchange rates were collected from a database of European Central Bank (ECB).

3.1.2 Descriptive statistics

Figure 7 represents the entry years of transactions in both samples. The entry years of transactions in full sample ranged from 1990 to 2015, while the most transactions were entered before the years of the financial crisis in 2008. In add-on sample, entry years ranged from 1999 to 2015. In both samples, the average entry year was 2005.

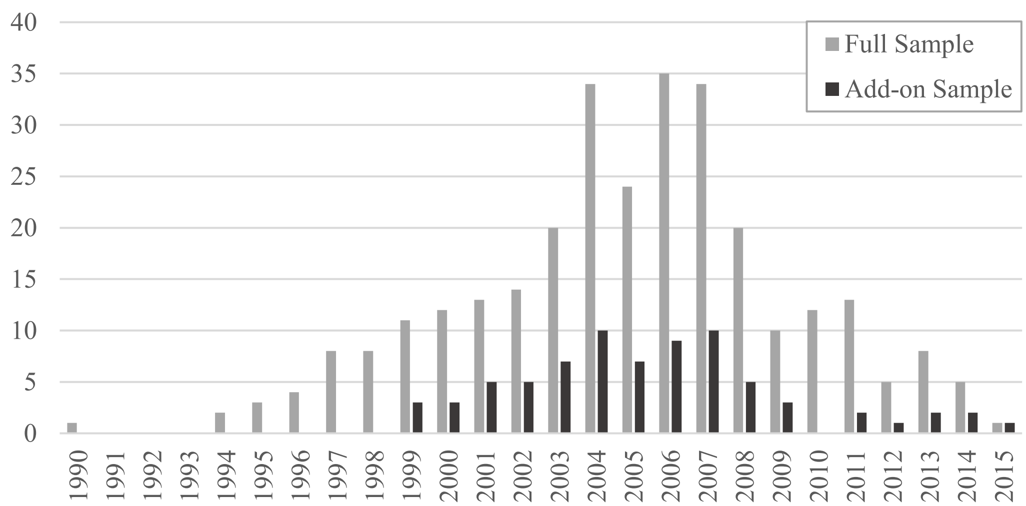


Figure 7 Transactions by entry year

Table 5 presents the descriptive statistics of both samples. The sample values reveal how both enterprise values and equity values grew on average in both samples. The mean enterprise and equity values are significantly lower in add-on sample, which is caused by the lack of add-on data provided by the GPs of the largest transactions. The amount of net debt decreased in full sample, while the mean slightly increased in add-on sample. The growth in net debt is partly explained by the additional debt raised to finance add-on acquisitions. However, debt/EV ratios decreased in both samples indicating that enterprise value growth exceeded debt growth also in add-on sample on average. EV/EBITDA multiples also raised significantly in both samples, which indicate that GPs were able to sell companies at a higher multiple than acquired on average.

Table 5 Descriptive statistics

	Full sample (*n*=297)			Add-on sample (*n*=75)		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Holding period	4.43	3.92	2.29	4.14	3.77	2.06
Times money	3.15	1.86	4.98	2.64	1.89	2.54
IRR	0.53	0.32	1.04	0.42	0.39	0.42
Public peer group size	53.23	21.00	87.68	66.44	26.00	105.73
Enterprise value (€m entry)	438.3	58.0	1194.6	103.3	57.2	106.7
Enterprise value (€m exit)	596.7	146.6	1167.3	231.9	146.6	235.2
Equity value (€m entry)	150.4	28.8	310.6	47.7	36.2	40.5
Equity value (€m exit)	359.9	89.5	766.1	167.0	100.2	168.6
Net debt (€m entry)	288.0	27.0	930.5	55.5	24.8	74.6
Net debt (€m exit)	236.8	24.6	538.1	64.9	24.0	91.8
EV/EBITDA multiple (entry)	7.33	6.69	4.02	8.42	7.42	5.15
EV/EBITDA multiple (exit)	9.01	8.40	6.91	11.20	9.23	6.96
Debt/EV ratio (entry)	0.55	0.60	0.25	0.44	0.52	0.30
Debt/EV ratio (exit)	0.32	0.25	0.29	0.26	0.30	0.20

3.2 Variables

Several assumptions needed to be made regarding the variables used at different stages of the data analysis process, and many related to the limitations of our dataset. First, our dataset only contained net debt values, while debt information was needed when calculating leverage ratios. Thus, an assumption needed to be made that net debt equals debt for all transactions. In practice, this means that cash and cash equivalents were assumed to be zero when calculating leverage. Although the effect of this assumption can not be expected to be intrinsically significant, it also has an effect on the equity values, which were calculated as the remainder of EV and net debt. Change in net debt was also used to estimate the generated free cash flow during a holding period. In addition to paying off debt and increasing cash and cash equivalents, the portfolio companies are likely to pay dividends during the holding period to its shareholders. However, our dataset did not contain data about dividends and thus those could not be included in the calculation of free cash flow.

One critical element of the IVC 2.0 framework is the separation of organic and inorganic value creation, which can be done in several ways. Usually, inorganic growth is assumed to be captured at the time of acquisition, and synergies as well as organic growth in acquired companies to be part of organic growth of the platform. However, one could also assume that the synergies and organic growth of acquired companies would be part of inorganic growth, since those would not have emerged without the acquisitions. This resembles the definition of intrinsic value creation introduced by Berg and Gottschalg (2005). Without having the detailed growth of each add-on company, we could have assumed equal percentual growth for portfolio company and acquired companies, and thus come up with an estimate of the second approach. However, to respect the original methodology (Zeisberger et al. 2016), we followed the common and simpler practice of capturing inorganic growth at the time of acquisitions.

Due to the methodology to capture inorganic growth, organic growth was calculated by subtracting acquired EV, net debt, sales and EBITDA values from the corresponding values of the portfolio company at exit. Value creation was separately calculated for organic and inorganic growth, as we will present in chapter 3.3.2. In an optimal situation, one would have data of the portfolio company before and after (pro forma) of each add-on acquisition to capture inorganic growth (Duff & Phelps 2014). However, our dataset only contained a sum of acquired values without dates or financial information of individual add-ons, and this forced us to make some assumptions. First, we assumed that the organic growth in portfolio company was linear during holding period. Second, we assumed that add-ons occurred in the middle of holding period on average. Using these assumptions, we were able to calculate valuation metrics of the portfolio company before and after add-on acquisitions and thus separate inorganic value creation.

Our manner to segregate incremental leverage and its contribution to value creation also merits comment. Previous studies, such as Puche et al. (2015), use average debt-to-equity ratio during holding period to separate the contribution of incremental leverage as introduced in chapter 2.4.1. However, we used the debt-to-EV ratio at entry since it better illustrates the risk appetite of GPs. Furthermore, using average debt-to-equity ratios led to several issues when separating inorganic growth and the contribution of industry. It could be argued that exit leverage ratios are subject to the generation of FCF, paying off debt and GPs' focus to sell the company rather than GPs' decision of maintaining a certain level of leverage. Using debt at entry of the investments thus better capitalizes the intended risk level of a GP and incremental effect when compared to industry peers. Furthermore, the manner in which previous studies have calculated average debt-to-equity ratios results in a biased view of the average debt during holding period as illustrated in the example calculation of chapter 3.3.2.

The assumptions regarding industry peer group selection also merit attention. First, we used standard industry classification (SIC) codes to match peer group companies with each transaction. SIC is a commonly used classification code among industry classification benchmark (ICB) which used by some other authors, such as Achleitner et al. (2011). We used the primary three-digit SIC code of a portfolio company to match peer group companies, but we reduced the length of SIC code up to one if comparable public companies were not found. The lack of companies was mostly caused by the significant differences in the sizes of different three-digit categories, and thus the relevance of peer group barely deteriorated when using shorter SIC codes.

While previous studies have not reported information about peer group sizes, we used five comparable companies as the minimum requirement for peer group selection. Furthermore, in addition to SIC codes, and entry and exit dates, we used Europe as the criteria for peer group companies. As suggested by Zeisberger et al. (2016) and Duff & Phelps (2014), we used weighted average values of peer group when calculating growth rates in various financial measures of industry. Thus, industry values can be seen as an alternative investment option in a weighted group of public comparable companies. This differs from the methodology of Achleitner et al. (2011) who used a median of industry. The means, medians and standard deviations of peer groups can be seen in the descriptive statistics of chapter 3.1.2.

3.3 Methods

3.3.1 IVC 2.0 framework

IVC 2.0 is a framework to decompose value creation and to allocate value creation to various sources of funding. The framework measures value creation across operational and financial levers separating the sources and causes of value creation. First, it generates a baseline investment return which illustrates the value that would have been generated with the capital structure of the average industry participant. In practice, this represents an investment in the portfolio company with a leverage ratio equal to the prevailing market value of the company at entry. Baseline investment is then divided into four categories of value creation: revenue, margin, multiple and cash flow. The four categories are further divided into changes in average industry participant, acquired value and alpha, which measures the abnormal value creation after controlling for industry change and add-on acquisitions. In multiple category, an additional lever is added to quantify the impact of multiple arbitrage resulting from differences in valuation multiples of parent and target companies. (Zeisberger et al. 2016)

The difference between baseline return and change in investment value is captured with the fifth category: capital structure. As high leverage is peculiar to buyouts aiming to boost equity returns, this category captures the effect of having more debt than the industry on average. Alternatively, a leverage ratio below industry average is captured with reduced return on equity due to increased equity financing. Capital structure effect is further divided into the effects of incremental interest expenses, incremental tax shield and total leverage effect. Since the five categories of framework measure the value creation to 100% equity owners, the framework further divides the change in total investment value into different sources of funding. (Zeisberger et al. 2016)

It should be noted that the methodology used in this thesis might not be precisely consistent with the original framework introduced by Zeisberger et al. (2016). Despite the introduction of the framework (Zeisberger et al. 2016) and our discussion with Mr. Bowen White – one of the authors – vague guidelines and lack of clear explanation about the several assumptions needed in the calculations might have resulted in small differences. Furthermore, the limitations of our dataset compelled us to make assumptions that may not be exactly aligned with the original framework. On the other hand, we aim to improve some of the expected limitations of the framework and develop a more comprehensive understanding of value creation by introducing persistence perspective. Due to the complexity of the framework, the methodology is presented through an example calculation of a fictional transaction in the following chapter 3.3.2.

To calculate value creation attribution, we build and used a python script to enable efficient data processing. The script was built to connect various sources of data and calculate the starting values of each transaction. Furthermore, the script matched comparable public companies with each transaction to calculate corresponding growth rates in the industry. Finally, the script calculated value creation attribution for each transaction according to the methodology of the following chapter.

3.3.2 Example calculation

The fictional transaction of this chapter introduces the methodology of the IVC 2.0 framework used in this thesis. Table 6 present financial measures of the fictional portfolio company at entry, during holding period and at exit. Enterprise value of the company is assumed to be EUR 100 million, the value of debt to be EUR 50 million, which equals to an equity value of EUR 50 million and a debt/EV ratio of 0.5 (50/100). Sales of the company are assumed to be EUR 100 million and earnings before interest, taxes, depreciation and amortization (EBITDA) to be EUR 10 million. Given these assumptions, EBITDA/sales margin is 10% (10/100) and EV/EBITDA multiple 10 (100/10). The fictional acquisition was executed 1/1/2012 and a PE fund acquired 70% of the company.

During holding period, the company paid EUR 10 million dividends to its shareholders and PE firm executed an investment of EUR 10 million to finance add-on acquisitions. Estimated interest rate was 9.0% during the holding period of 4 years, resulting in a total cost of debt of 41.2% ((1 + 0.09)^(4) – 1). Average tax rate during the holding period was 30%.

Table 6 Transaction values

	Entry	*Holding period*	*Exit*	*Acquired*	*Organic delta*
Enterprise value (€m)	100		165	25	40
Equity (€m)	50		140	15	75
Debt/net debt (€m)	50		25	10	-35
Sales (€m)	100		120	10	10
EBITDA (€m)	10		15	2	3
EBITDA/Sales	10.0 %		12.5 %	20.0 %	1.8 %
EV/EBITDA	10.0x		11.0x	12.5x	0.8x
Free cash flow (€m)					45
Debt/EV	0.50				
Dividends (€m)		10			
Capital Injections (€m)		15			
Interest rate		9%			
Holding period [years]	01/01/2012	4.0	01/01/2016		
Cost of debt		41.2 %			
Tax rate		30.0 %			
PE ownership	70%				

At exit, the company's equity value had increased to 140 million and value of debt to EUR 25 million, equalling to an enterprise value of EUR 165 million. Sales grew to EUR 20 million and EBITDA to EUR 15 million, resulting in EBITDA/sales margin of 12.5% (15/120) and EV/EBITDA multiple of 11 (15/165) at exit. Part of the growth, however, was achieved as a result of add-on acquisition executed during the holding period, reducing the organic growth of the portfolio company. A total enterprise value of EUR 25 million was acquired, of which EUR 15 million was financed with additional debt and EUR 10 million with equity injections of PE investor. Total acquired sales were EUR 10 million and EBITDA EUR 2 million, resulting in EBITDA/Sales margin of 20.0% (2/10) and EV/EBITDA multiple of 12.5 (25/2) for the acquired entity.

The organic delta column of table 6 presents the organic growth in financial measures after subtracting the effect of add-on acquisitions. For example, organic delta in equity value was EUR 80 million ((140 – 50) – 10) and organic growth in

EBITDA EUR 3 million ((15 – 10) – 2). Total free cash flow of a company's organic activities is calculated as the sum of change in net debt and dividends paid to shareholders (40 + 10 = 50).

To separate inorganic value creation resulting from add-on acquisitions, the value of the portfolio company is needed both before the acquisition and right after acquiring the company (pro forma). Table 7 represents how the framework captures inorganic value creation. At the time of acquisition, the enterprise value of the company was EUR 120 million, consisting of EUR 88 million of equity and EUR 33 million of debt. Sales were EUR 105 million and EBITDA EUR 11.5 million resulting in EBITDA/Sales margin of 11.0% and EV/EBITDA multiple of 10.

Table 7 Acquired values

	Acquired	*Parent*	*Pro forma*	*Delta*
Enterprise value (€m)	25	120	145	25
Equity (€m)	15	88	103	15
Debt/net debt (€m)	10	32.5	42.5	10
Sales (€m)	10	105	115	10
EBITDA (€m)	2	11.5	13.5	2
EBITDA/Sales	20.0 %	11.0 %	11.7 %	0.8 %
EV/EBITDA	12.5x	10.4x	10.7x	0.3x
PE ownership	15%		60%	

The values after add-on acquisitions (pro forma) have calculated as the sum of the corresponding values of parent and acquired entities. EBITDA/Sales margin and EV/EBITDA multiple values have been calculated from the underlying values. Delta column captures the changes in parent company resulting from the add-on acquisitions. Furthermore, the ownership of initial investment is diluted as a consequence of issuing new shares to equity injectors. The ownership of follow-on funder is 15% (15/103) while the ownership of initial PE investment decreases to 60% (70%*88/103).

Table 8 presents the financial values of comparable public companies during the holding period of the fictional investment. Enterprise value, equity, debt and sales values are presented as the sums of all comparable public companies found based on the matching criteria presented in chapter 3.2. In this example, the total enterprise value of public peers was EUR 3,000 million, total equity EUR 2,000 million, debt EUR 1,000 million, sales EUR 2,000 million and EBITDA EUR 400 million at entry, resulting in weighted average EBITDA/Sales margin of 20.0%and EV/EBITDA multiple of 7.5 at entry. At the exit year of investment, the total enterprise value was EUR 3,200 million, equity EUR 2,400 million, debt EUR 800 million, sales EUR 2,200 million and EBITDA EUR 400 million, resulting in EBITDA/Sales margin of 18.2% and EV/EBITDA multiple of 8.0. Delta column captures the changes in each value during the holding period of the investment. Furthermore, the total free cash flow during holding period was EUR 300 million, which consisted of change in net debt and dividends paid during the holding period (200 + 100).

Table 8 Industry values

	Entry	*Holding period*	*Exit*	*Delta*
Enterprise value (€m)	3000		3200	200
Equity (€m)	2000		2400	400
Debt/net debt (€m)	1000		800	-200
Sales (€m)	2000		2200	200
EBITDA (€m)	400		400	0
EBITDA/Sales	20.0 %		18.2 %	-1.8 %
EV/EBITDA	7.5x		8.0x	0.5x
Free cash flow (€m)		300		
Debt/EV	0.33			
Dividends (€m)		100		

Tables 6–8 present all financial values of the fictional transaction during different times of holding period needed in the calculations of the methodology. Table 9 below illustrates how value creation was attributed to different equity holders and how the incremental effect of leverage was captured. First, the total change in

investment value was captured as a sum of organic change in equity value and dividends. Investment value was further divided into different equity owners according to diluted ownerships at exit.

Table 9 Change in investment value and baseline return

	EUR m	TM points
Δ Investment Value	**85.0**	**1.3**
Other investors	21.6	0.3
Follow-on	12.4	0.2
Initial	51.0	0.8
Capital Structure	**21.3**	**0.3**
Leverage Effect	24.9	0.4
Tax Shield	1.5	0.0
Interest	-5.1	-0.1
Δ Baseline	**63.8**	**1.0**

To extract the effect of incremental debt, baseline investment return was extracted by applying the capital structure of average industry participant to the portfolio company. In practice, this represents an investment in the portfolio company with a leverage ratio equal to prevailing market value at entry. We calculated the investment ratio using the following formula:

$$Investment\ ratio = \frac{1 + \frac{D_t}{EV_t}}{1 + \frac{D_i}{EV_i}}, \text{where}$$

$\frac{D_t}{EV_t}$ = debt to enterprise value ratio of portfolio company

$\frac{D_i}{EV_i}$ = weighted average debt to enterprise value ratio of industry.

In the case of our fictional transaction, the investment ratio was 75% ((1 + 0.5)/(1 + 0.33)). Thus, the enterprise value of the fictional investment at entry would be EUR 75 million (100*0.75%) and debt EUR 25 million (75 – 50), resulting from the original equity value of EUR 50 million. By applying the investment ratio to the total investment returns, baseline return can be calculated using the following formula:

$$\textit{Baseline return} = \textit{Investment ratio} * \textit{(change in equity + dividends)},$$

which in this case results in a baseline return of EUR 63.8 million (75%*(75 + 10)). The capital structure effect is captured as the difference between change in investment value and baseline return, resulting in a capital structure effect of EUR 21.3 million in the case example. Since incremental debt has also resulted in higher interest expenses, an additional lever is added to extract the effect of incremental cost of debt on value creation. Furthermore, tax shield lever captures the effect of reduced interest expenses due to tax shield using transaction specific tax rate. The net effect of incremental debt and tax shield is captured as FCF effect. The increased return on capital due to reduced equity financing is then captured with leverage effect driver. TM values were calculated by dividing monetary value creation by the total invested capital.

It should be noted that the way in which the framework captures incremental debt is significantly different from the methodologies presented in previous literature. For example, the formula of Achleitner et al. (2010) presented in chapter 2.4.1 is based on estimated average debt-to-equity ratio during the holding period. It could be argued that the manner in which their methodology captures incremental debt is thus subject to a portfolio company's ability to create FCF and pay off debt during the holding period rather than GPs decision as in the case of IVC 2.0 framework, which uses debt/EV ratio at entry. Furthermore, for example Puche et al. (2015) calculate average the debt-to-equity ratio simply as the average of entry and exit debt-to-equity ratios, which often results in biased results of average debt. For example, in our case, their method to capture average D/E would result in a ratio of 0.56 while using average equity and average debt to calculate the ratio would result in 0.37. Furthermore, the severity of the consequences of their simplification increases when D/E ratios are compared to industry averages to capture incremental debt.

By applying the investment ratio to the financial values of the portfolio company, baseline return can be divided into different sources of value. Our methodology to capture the effect of total revenue, margin, multiple and cash flow reminds the more conventional method of Puche et al. (2015). First, the cash flow driver can be calculated using investment ratio and FCF generated during holding period, resulting in EUR 33.8 million (75%*45). Cash flow driver is divided into industry and alpha drivers by comparing the company's free cash flow generation to the average of industry peers. The original idea of IVC 2.0 framework is to make this division by comparing annual cash flow growth rates (Write et al. 2016). Since we did not have annual free cash flow information in our data, we had to come up with an alternative way to compare a transaction to industry. We used a ratio between annual average FCF during holding period and entry sales to get comparable rates between a transaction and industry. In our case example, the ratio was 11.3% for the transaction and 3.8% for the group of industry peers. Thus, 33% (3.8%/11.8%) of FCF generation was attributed to industry while the remaining 67% was attributed to alpha.

The total contributions of margin, revenue and multiple were captured in a conventional manner. For example, the contribution of multiple was captured by multiplying the entry EBITDA with the change in multiple and investment ratio (10*0.8*75%), resulting in multiple contribution of EUR 5.8 million. The contribution of margin and revenue was calculated in a similar manner. The first column of table 10 illustrates how the industry leverage adjusted baseline return was divided into these drivers.

The contribution of each operational improvement driver was further divided into industry and alpha drivers by comparing the annual growth rates between a transaction and industry. For example, the annual sales growth rate was 2.4% for both the transaction and industry, and thus revenue growth was fully attributed to industry. An exception is made in alpha multiple driver, where value creation is further divided into organic and inorganic drivers. Inorganic value creation represents multiple arbitrage resulting from the difference between parent's and targets valuation multiples.

Table 10 Value creation attribution of baseline return

	EUR m	EUR m	TM points
Δ Baseline	**63.8**	**63.8**	**1.0**
Cash Flow	**33.8**	**15.0**	**0.2**
Alpha	22.5	22.5	0.3
Industry	11.3	11.3	0.2
Δ Multiple	**5.8**	**6.1**	**0.1**
Organic	3.8	4.1	0.1
Inorganic	-3.1	-3.3	-0.1
Industry	5.0	5.3	0.1
Comb. EBITDA & Multiple	1.7		
Δ Margin	**13.6**	**15.4**	**0.3**
Alpha	21.2	23.9	0.4
Industry	-7.5	-8.5	-0.1
Δ Revenue	**7.5**	**8.5**	**0.3**
Alpha	0.0	0.0	0.0
Industry	7.5	8.5	0.1
Comb. Revenue & Margin	1.4		

As discussed in chapter 2.4.1, simultaneous changes in EBITDA and multiple, and margin and revenue result in combination effects. While these effects are often baked into main drivers causing biased results or reported as separate drivers (see for example Puche et al. 2015), we decided to follow an alternative approach. Since reporting these values as separate drivers would have increased the complexity of the framework and thus made it more difficult to understand, we decided not to report these as separate drivers, following also the idea of the original IVC 2.0 framework (Zeisberger et al. 2016). However, the Zeisberger et al. (2016) do not report how combination effects should be treated and it is thus likely that these effects are baked into main drivers. For example, common industry practice is to allocate combination effect resulting from simultaneous changes in multiple and EBITDA to multiple driver, which overstates the contribution of this driver (Zeisberger et al. 2016). To avoid this bias, we allocated the combination effects to all underlying drivers according to their original contributions, as can be seen in the second column of table 10. For example, the total contribution of organic multiple driver increased from EUR 3.8 million to EUR 4.1 million as a result of combination effect allocation (3.8 + 1.7*(3.8/(5.8 + 13.6 + 7.5)) = 4.1). Although this methodology could be criticized, we were able to simplify the methodology and respect the relative contribution of each driver.

While the previous calculation represents the organic value creation of a transaction, the acquired value creation was separately calculated. Table 11 below illustrates how acquired value creation was captured from the acquired values of table 7. In general, acquired value creation was calculated similarly as organic value creation. Also, the combination effect of acquisitions was separately calculated and allocated to underlying drivers according to their contribution in the first column of table 11. The IVC 2.0 framework assumes that acquired multiple, margin and revenue components are offset by the financing of the acquisitions. Thus, the only acquired driver creating value is the multiple arbitrage driver resulting from the difference between the valuation multiples of acquired entities and parent company. In our example, the acquired multiple was 12.4 versus a multiple of 10.4 of the parent company, which resulted in a negative multiple arbitrage effect of EUR -3.3 million or TM of -0.1.

Table 11 Inorganic value creation

	EUR m	EUR m	TM points
Acquisition Finance	**-18.8**	**-18.8**	**-0.3**
Multiple arbitrage	-3.3	-3.3	-0.1
Multiple	2.6	2.7	0.0
Comb. EBITDA & Multiple	0.5		
Margin	6.5	6.9	0.1
Revenue	8.6	9.1	0.1
Comb. Revenue & Margin	0.6		

Figure 8 illustrates the total value creation of the fictional transaction. In practice, it merges the organic and acquired value creation represented in tables 9–11, using TM as a unit. TM values were calculated by dividend the monetary contributions with total invested capital, which consists of entry equity and additional capital injections during the holding period (50 + 15 = 65).

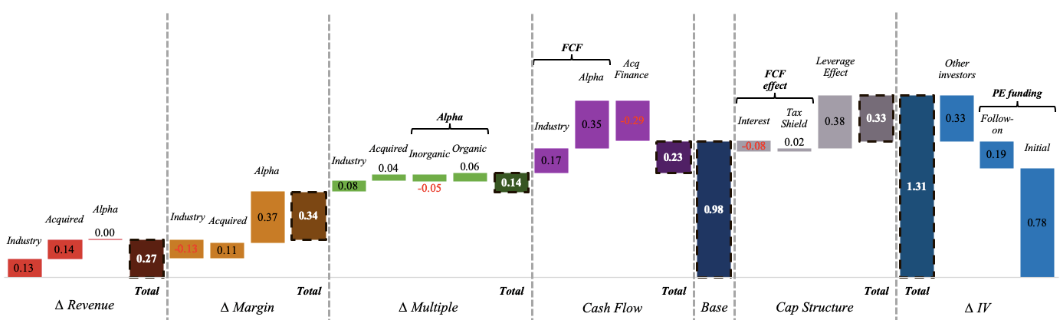


Figure 8 Value creation of the fictional transaction

In the example transaction, the net effect of using higher leverage than industry represented 25% (0.33/1.31) of total value creation. The remaining 75% of value creation was generated with operational improvements and multiple expansion. The most significant driver was margin improvement (0.34), while the contribution of revenue growth was also remarkable (0.27). However, a closer examination of the sources of these drivers reveals that the difference in GP specific contributions (alpha) was even greater. Alpha margin contribution was 0.37 and industry margin -0.13 indicating that the transaction outperformed industry peers significantly in margin improvements. In revenue growth, however, alpha revenue was zero meaning equal growth in portfolio company and industry.

The total contribution of multiple growth on value creation was 0.14. Despite the negative multiple arbitrage effect resulting from add-on acquisitions, the total alpha contribution was positive (0.06). Acquisitions also increased the multiple of the platform resulting in a contribution of 0.04. The significant multiple growth in the industry resulted in an industry multiple contribution of 0.08. The total effect of FCF after subtracting the financing of acquisitions was 0.23. The majority of FCF generation was attributed to alpha, resulting in a contribution of 0.35 compared to industry driver of 0.17.

3.3.3 Measuring persistence

Scholars studying performance persistence have introduced several alternative methodologies to examine the ability of GP to exhibit constant performance. Studies focusing on quartile performance have used Markov transition matrices (see for example Aigner et al. 2008 and Harris et al. 2014a), which measure the likelihood of a GP's follow-on fund to stay in the same or move to other performance quartile compared to the GP's precedent fund. This methodology thus separates the persistence between top and low-performing funds, highlighting the difference of persistence between different performance levels.

Most commonly, researchers have studied persistence using correlations of two consecutive funds of a GP (Braun et al. 2017b, Buchner et al. 2016). However, this methodology only measures the correlation between two data points – either the performance of a fund or the return of individual transaction – thus focusing only on short term persistence (Braun et al. 2017b). To mitigate this issue, some authors have studied the correlation with the funds before the preceding fund (see for example Kaplan and Schoar 2005). At deal-level, however, too many preceding transactions would be needed to understand the long term persistence of a GP. Furthermore, since we have several value creation drivers instead of the total return of a fund or transaction, this approach would result in far too complex results.

To enable studying the persistence of several value creation drivers, we selected the approach of Braun et al. (2017b). They study the fixed effect of a GP on the variation of a specific driver to determine how much of the variation is explained by the GP of a transaction. First, we use standard deviation to demonstrate the volatility of a driver in general:

$$\sigma_r = \sqrt{\frac{\sum_{i=1}^{n}(x_{ir} - \bar{x}_r)^2}{n-1}}, \text{where}$$

σ_r = standard deviation of driver *r*,
x_{ir} = value contribution of transaction *i* with driver *r*,
$\bar{x}_r$ = mean contribution of driver *r*,
n = sample size.

To extract the fixed effect of GP, we subtract the average contribution of a GP from each driver value to separate the variation within GPs from the variation between GPs:

$$\sigma_r = \sqrt{\frac{\sum_{i=1}^{n}((x_{ir}^m - \bar{x}_r^m) - \bar{x}_r)^2}{n-1}}, \text{where}$$

σ_r = standard deviation of driver *r*,
x_{ir}^m = value contribution of transaction *i* of GP *m* with driver *r*,
$\bar{x}_r^m$ = mean contribution of driver *r* in the transactions of GP *m*,
$\bar{x}_r$ = mean contribution of driver *r*,
n = sample size.

Furthermore, since the mean contributions of drivers vary significantly, we divide the standard deviation with the mean contribution of a driver to have comparable persistence measures for different sized value creation drivers. Since some contributions are negative, we use the means of absolute values of contributions. The resulting value is the coefficient of variation (CV), which we use as the measure of persistence:

$$CV_r = \frac{\sigma_r}{\frac{\sum_{i=1}^{n} |x_{ir}|}{n}}, \text{ where}$$

σ_r = standard deviation of driver *r*,
x_{ir} = value contribution of transaction i with driver *r*,
n = sample size.

We calculate the values of CV both before and after controlling for the fixed effect of GP, to understand the total variation in a driver's contribution and the average variation within GPs. Furthermore, we use the ratio of the two CVs to illustrate how much of the variation is explained by the differences between GPs and how much of it remains within GPs. To validate the reliability of our results, we use F-test to estimate the two-tailed probability that the differences in standard deviations before and after GP fixed effect are not significantly different.

4. Results

4.1 Value creation

4.1.1 Full sample

Figure 9 shows the average value creation of the full sample containing 297 private equity transactions. The average change in investment value was 3.15, which means that on average, the equity values of the companies have more than quadrupled under PE ownership. The average return is in line with the results of Puche et al. (2015), whose final sample of over 1,300 European transactions yielded a TM of 3.3. 59% (1.87/3.15) of the change in investment value captured by initial investment and only 0.3% through follow-on funding. Remaining 40% was captured by other investors, such as portfolio companies' management.

In line with the results of the previous studies, a great share of value creation was achieved by using more leverage than industry peers. On average, incremental leverage yielded a TM of 1.27, accounting for 40% of the total value creation. The relative share of incremental leverage is in line with the findings of previous studies (Acharya et al. 2012, Ernst & Young 2014, Puche et al. 2015), although the previous results are not fully comparable due to methodological differences to extract the contribution of incremental leverage. The total leverage effect in our sample was 1.53, but a TM of 0.36 was captured by debt holders. Tax shield increased the returns with a TM of 0.10 on average.

Incremental debt financing decreased baseline – value creation with average industry leverage – to a TM of 1.88. This means that in theory, the companies would still have almost tripled in size during PE ownership if financed with the average capital structure of the industry. The generation of cash flow had a low contribution to value creation, averaging 0.10. The role of generating FCF in our sample was thus significantly lower than in the sample of Puche et al. (2015) who averaged a contribution of 0.4 for European transactions. However, our methodology reveals that portfolio companies were still generating significantly more cash flow than public comparable companies: industry FCF contribution was only 0.02 while alpha FCF was 0.08.

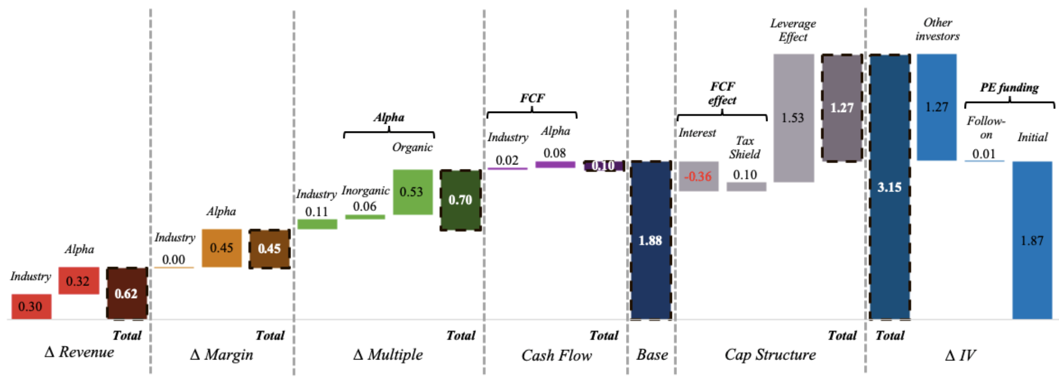


Figure 9 Average value creation attribution of full sample

Multiple improvement was the largest single value creation driver with a contribution of 0.70. With a relative contribution of 22% (0.70/3.15), the contribution of multiple change is a little higher than the multiple effect of 15% reported by Puche et al. (2015), although part of the difference is attributable to separately reported combination effect of 6%. Our results show that the contribution of industry multiple growth was only 0.11 while alpha multiple contribution was 0.59 in total. Most of the alpha (0.53) was attributable to organic multiple growth indicating that GPs are able to increase valuation multiples more on average than public comparable companies. Furthermore, inorganic multiple contribution of 0.06 indicates that GPs are able to increase the multiples of acquired entities as part of the platform of portfolio company.

Margin improvement was another significant value creation driver with an average contribution of 0.45. Margin improvements were fully attributable to alpha, leaving zero contribution to industry on average. The results indicate that while GPs invested in industries where public comparable companies did not improve profitability on average, GPs were able to create significant value by improving profitability. The relative contribution of 14% (0.45/3.15) is slightly higher than margin effect of 8% and combination effect of 1% reported by Puche et al. (2015).

Increasing the revenues of portfolio companies contributed a TM of 0.62 to value creation on average. The relative contribution of 20% (0.62/3.15) is lower than 27% reported by Puche et al. (2015). The role of industry development was the greatest in revenue driver: almost half of the value created through increasing revenue was attributable to growing industry (0.30) while remaining 0.32 was attributable to alpha. This means that PE-backed companies were still able to grow revenue more than twice as fast as public peers but were also able to select target companies from growing industries.

In addition to organic value creation, portfolio companies executed add-on acquisitions to create value. Figure 10 reports the value creation of add-on acquisitions. The results reveal that a significant amount of revenue growth was achieved with add-on acquisitions, equalling to a contribution of 0.12. Margin contribution was 0.00 indicating that acquired companies were equally profitable as platform companies on average, thus not creating value at the time of acquisition. Despite the manner of the framework to capture acquired value at the time of acquisition, part of alpha margin can be expected to be attributable to synergies realized by the add-ons, thus increasing the value created with add-on acquisitions.

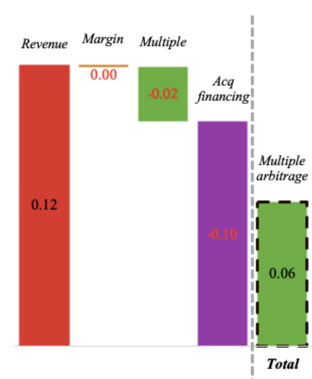


Figure 10 Average inorganic value creation of full sample

The contribution of multiple was -0.02 indicating that add-on acquisition had a small negative effect on portfolio companies' valuation multiple on average. The contributions of acquired revenue, margin and multiple are fully offset with acquisition financing since they are not considered to create value in the framework. Instead, multiple arbitrage is the only inorganic value creation driver, which averaged a TM of 0.06 in our sample. The contribution of multiple arbitrage is thus only inorganic value creation driver in the value bridge of graph 9.

While the previously introduced results reveal interesting insights about value creation in a large sample of PE transactions, the partly missing add-on data of transactions cause minor bias in the results. In practice, lack of add-on data results in the allocation of conceivable add-ons into different levers of alpha, overstating these organic value creation drivers and thus the outperformance of GPs over public peers. Furthermore, the lack of information about conceivable equity injections used to fund add-on acquisitions increases the total TM returns of equity owners. To avoid these issues, we will next analyse the subset of transactions containing full information about add-ons.

4.1.2 Add-on sample

Add-on sample consists of the 75 transactions of full sample, where full add-on data was available. In 51 of these transactions, one or more add-ons were executed while zero add-ons were reported for the remaining 24 transactions. The total change in investment value was 2.64 on average, which is lower than the average of full sample, but expected due to capital injections used to fund add-ons. 67% (1.77/2.64) of the value creation was captured by PE investors, of which 2% (0.04/1.73) was attributable to follow-on funding. Remaining 33% was captured by other investors. The average value creation of add-on sample can be seen in figure 11.

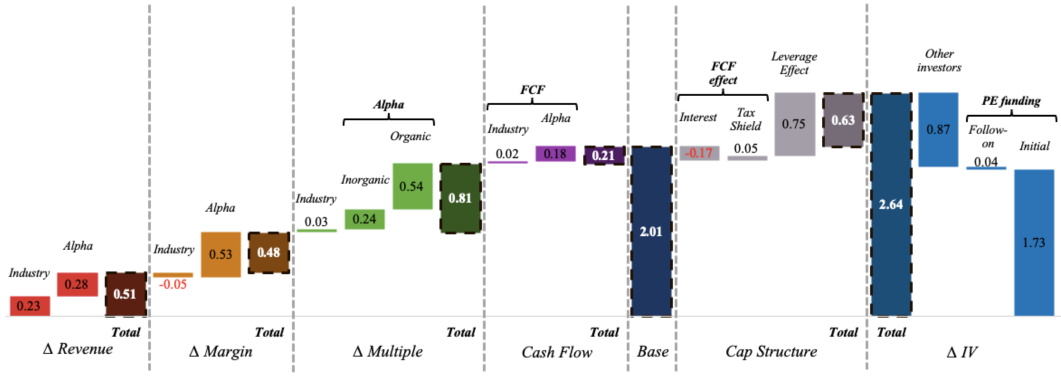


Figure 11 Average value creation attribution of add-on sample

The average contribution of leverage was significantly lower than in full sample. This may be due to the significantly lower average enterprise value of full sample, causing decreased access to debt financing. The results of Puche et al. (2015) could explain the phenomenon since they show that the contribution of leverage is significantly higher in larger transactions. The total effect of leverage was 0.82, of which 0.27 was paid as interest expenses and 0.08 was saved as reduced taxes. After controlling for industry leverage, transactions yielded a baseline of 2.01 on average, meaning tripling the equity value of portfolio companies on average.

The contribution of cash flow in add-on sample was 0.21, the majority of which was attributable to alpha. While the relative contribution was higher than in full sample, it was still lower than the average reported by Puche et al. (2015). Multiple growth was the largest contributor to value creation with a TM of 0.81. Closer examination of the causes of multiple growth reveals that majority of multiple growth was achieved through alpha, leaving only a TM of 0.03 to industry contribution. Alpha multiple of 0.78 was achieved through both organic multiple growth and multiple arbitrage, and organic growth represented roughly two-thirds of the total alpha contribution. The results indicate that GPs are able either to buy with cheaper or sell with higher multiples than market on average. Furthermore, GPs are able to create value by integrating add-on targets with lower valuation multiples as a part of the platform of a portfolio company.

The contribution of revenue growth and margin improvement were roughly equal in add-on sample with contributions of 0.51 and 0.48, respectively. Margin improvements in portfolio companies were significantly higher than in public peers which decreased EBITDA margin on average. The contribution of alpha was 0.53 while industry yielded a negative contribution of -0.05 on average. Revenue growth driver was more equally split to industry and alpha drivers with contributions of 0.23 and 0.28, respectively. The results indicate that on average GPs are able to select targets from growing industries but not from industries where profitability is expected to grow on average.

Rearranging value creation to three sources of value reveals the importance of alpha in value creation. Figure 12 shows that the total contribution of alpha was 1.77 on average while industry growth contributed only a total of 0.24. The largest driver of alpha was the change in valuation multiple, which resulted in a total average TM of 0.77. The second largest driver was margin with a contribution of 0.53. Thus, almost 75% of the leverage-adjusted outperformance is explained by multiple growth and margin improvement. The result is interesting and partly conflicting with the previous finding suggesting that GPs focus on revenue growth rather than margin improvements (Kaserer 2011, Puche et al. 2015).

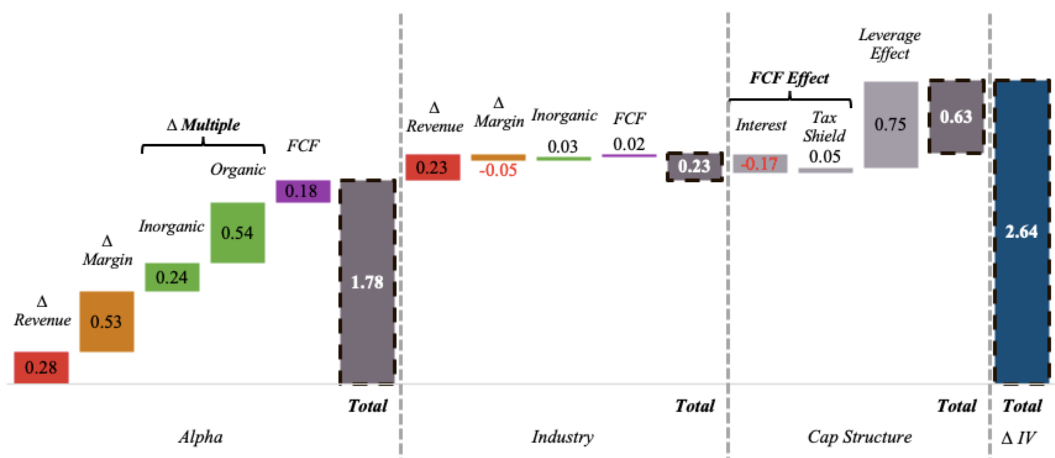


Figure 12 Rearranged value creation of add-on sample

Figure 13 reveals the contribution of add-ons in value creation. The average contribution of acquired revenue growth was significant, equalling to an acquired revenue driver of 0.48. Acquired margin contribution was zero on average meaning that the profitability of add-ons was equal to portfolio companies on average. The contribution of acquired multiple was negative on average, which indicates that add-ons decreased the valuation multiples of platforms on average. The three drivers were offset by the financing of acquisitions. Despite the negative effect of acquired multiple, the contribution of multiple arbitrage was 0.24, representing the only inorganic value driver in the value bridge of figure 12 and figure 13.

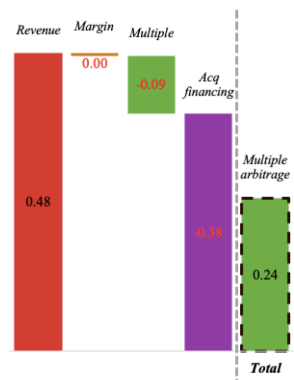


Figure 13 Inorganic value creation of add-on sample

Figure 14 combines the organic value creation of figure 11 with the acquired values of figure 13. The value bridge reveals that roughly a half (0.48/0.99) of revenue growth in portfolio companies was achieved through inorganic revenue growth. The actual contribution of GP was thus relatively low, representing only 28% (0.28/0.99) of total revenue contribution. However, in margin improvements, the contribution of organic alpha was remarkable, representing 110% (0.53/0.48) of margin value creation. In multiple growth, add-ons decreased the multiples of platforms on average, but multiple arbitrages raised the net multiple effects of add-ons to positive.

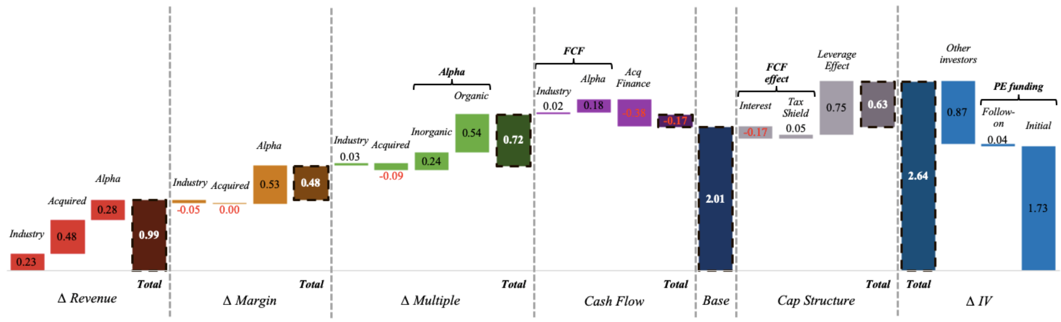


Figure 14 Full value creation attribution of add-on sample

Due to the methodology of IVC 2.0 framework to capture inorganic value creation at the time of acquisition, the actual contribution of add-on acquisitions is likely to be greater than value contribution of multiple arbitrage. For example, the integration of add-ons as a part of the platform of portfolio companies is likely to result in synergies, which are captured by alpha margin driver. Thus, a part of the alpha margin driver is likely to be achieved as an indirect consequence of add-ons. Our results could explain the findings of Söffge and Braun (2018) who found that revenue growth is a significant driver only for organic deals. Our result indicates that while a significant part of revenue growth is acquired – and thus does not create value itself – the value is captured as margin improvements resulting from capturing cost synergies.

Furthermore, as add-ons increase the size of the portfolio company and thus can be expected to decrease the bankruptcy risk of the platform on average, add-ons are likely to contribute to organic multiple growth. Thus, the contribution of GPs' skill to negotiate lower multiples at entry and higher multiples at exit is likely to be smaller than the organic multiple driver. For example, Achleitner et al. (2011) found sales growth to have a positive effect on exit multiples which supports this result.

In general, both samples highlight the role of incremental leverage and multiple expansion in value creation. Also, the contributions of revenue growth and margin improvements are significant, while the generation of FCF seems to have a minor role in value creation. When examining the GP specific drivers, leverage effect is the most significant driver while the contributions of multiple growth and margin improvement are also significant. Alpha revenue growth and alpha FCF seem to have a smaller role in value creation on average. Incremental leverage, multiple expansion and margin growth thus appear as the most auspicious drivers when examining the persistence of value creation.

4.2 Persistence

4.2.1 Volatility of value creation drivers

While the results of the previous chapter represent the average contributions of each value creation driver, it does not reveal how much variation was in the drivers' contributions. The lower the variation, the more a driver could be seen as a consequence of a GP's skill rather than pure luck. Furthermore, there is no reason to assume that the contributions of drivers are normally distributed which raises the question of whether the mean of a driver is in the middle or closer to one end of the distribution.

Figure 13 represents the average contributions and a 95% confidence interval of each value creation driver in add-on sample. For simplicity, acquired value creation has been removed from this representation. First, total investment value change ranged from a negative contribution of -0.4 to 10.4 with the confidence of 95%, and thus the mean contribution of 2.6 was significantly closer to the lower end of the contribution. This implies that some transactions generate significantly higher returns than the average. A similar pattern is present in baseline return, although the mean is lower at 2.0. However, the mean contribution of leverage is slightly over the middle of the 95% confidence interval.

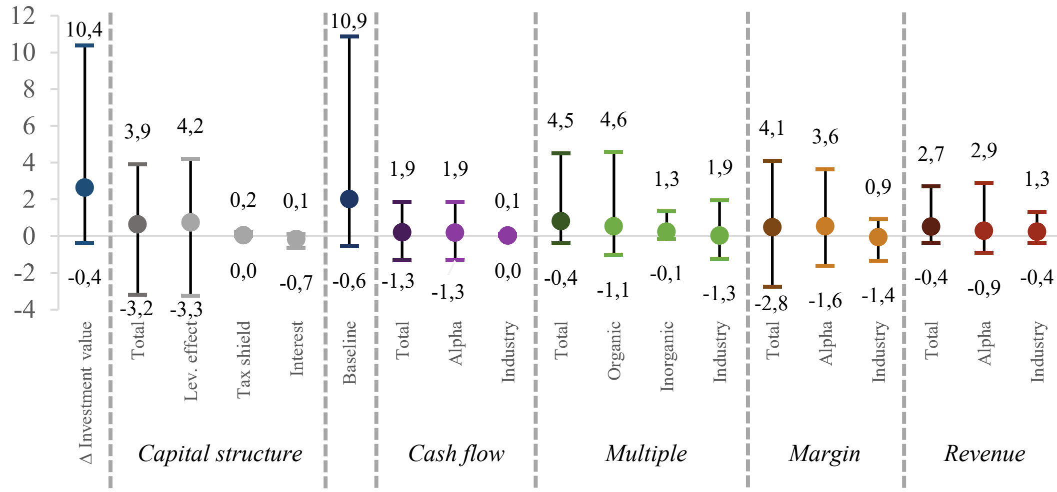


Figure 15 Mean contributions and a 95% confidence interval of value creation drivers in add-on sample

In cash flow and margin drivers, the mean contribution is close to the middle of the distributions. This implies, that the medians of these distributions are close to mean value, and at the confidence of 95%, both negative and positive changes from mean are roughly equal. While the variations are clearly dependent on the average contribution, negative contributions in margin driver seem much more likely than in multiple driver, despite the lower mean contribution of margin. In multiple and revenue drivers, the sample mean is close to the lower end of the distribution, indicating that worst performers are still relatively close to the mean values. On the other hand, some transactions have been able to significantly outperform mean contributions in multiple expansion and revenue growth.

Since the standard deviations of figure 13 are clearly dependent on mean contributions, it would be interesting to examine which drivers' volatility is low compared to the average contribution to identify relative persistence of these drivers. Furthermore, the distributions raise questions about whether the variation occurs between or within the GPs. For example, the transactions creating outperforming returns in multiple expansion and revenue growth might be explained by skill of a specific GP or GPs or might be pure luck of selecting high performing targets by random GPs. In the following chapters, we will take a closer look into the persistence of these drivers.

4.2.2 Relative persistence and dependency on GP

Table 12 below illustrates the coefficient of variation (CV) in different drivers before and after controlling for GP fixed effect. Total column represents the variation in the total sample while GP fixed effect column captures the average variation within GPs. The value of CV for the total return was 1.46 in full sample and 0.94 in add-on sample. CVs decreased to 1.35 and 0.85 after controlling for GP fixed effect, which indicates that GPs explain variation in total returns to some extent.

The CV value of total return is the lowest in both samples, and thus it seems to be more persistent than other drivers on average. The only exception is industry leverage adjusted baseline return, which CV was 1.40 and 1.27 after controlling for GP fixed effect in full sample. The value of 0.10 in the F-test supports the reliability of the result. The result indicates that industry leverage adjusted return is more persistent driver than total return and might thus be a better predictor of GPs' ability to create value.

Of the five main value creation categories, revenue growth seems to be the most persistent value creation driver. The CV value of total revenue driver was 1.67 in full sample and 1.08 in add-on sample, while those decreased to 1.55 and 1.00 after controlling for GP fixed effect. The sub-drivers of revenue indicate lower persistence than the total revenue driver. However, acquired revenue growth seems to be the most persistent driver in add-on sample, while the persistence of alpha revenue growth seems to be low. Thus, the results indicate that high persistence is driven by acquired and industry growth rather than GP specific alpha. The high variation of acquired revenue driver in full sample is explained by the lack of add-on data in some transactions.

The persistence of capital structure effect, cash flow generation and multiple growth seem roughly equal on average. The CVs of capital structure were 1.77 and 1.51 and decreased to 1.61 and 1.33 after controlling for GP fixed effect. Furthermore, the total effect of incremental leverage seems to have even lower volatility both before and after controlling for GP fixed effect. The CV in the contribution of cash flow was 1.82 and 1.52 and decreased to 1.68 and 1.31 after controlling for GP fixed effect. The sub-drivers of cash flow demonstrate even lower persistence than total cash flow indicating that to some extent, GPs are able to consistently select industries generating significant cash flow and also consistently generate more cash flow than industry peers.

The CV for multiple contribution was 1.78 for both samples and decreased to 1.56 and 1.34 after controlling for GP. The persistence of organic multiple growth was even greater indicating that organic multiple growth is more persistent driver than total multiple growth. Furthermore, GPs' ability to select industries with growing multiples was more persistent than total multiple growth in full sample. In add-on sample, the exploitation of multiple arbitrage and acquired multiple growth also showed some indication of persistence. The high variation in the corresponding drivers in full sample is explained by the lack of add-on data in some transactions.

Finally, margin growth seemed to be evidently the least persistent driver of the five main categories. The CV of total margin effect was 2.27 in full sample and 2.06 for full sample, and decreased to 2.17 and 1.98 after controlling for GP fixed effect. Within the sub-drivers of margin, most drivers indicated even less persistence. In full sample, investing in industries with increasing profitability seemed to be a slightly more persistent driver than total margin effect, but variation was still high when compared to other categories' drivers. Add-on sample indicates that GPs' ability to outperform industry profitability growth and acquiring more profitable add-ons were slightly more persistent than total margin effect on average.

Table 12 Coefficient of variation (CV) of value creation drivers

	Coefficient of variation (CV)							
	Full sample				Add-on sample			
	Total	Total - GP fixed	Ratio	F-test	Total	Total - GP fixed	Ratio	F-test
Δ Inv. Value	**1.46**	**1.35**	**0.93**	**0.19**	**0.94**	**0.85**	**0.91**	**0.40**
Other Investors	1.90	1.80	0.95	0.34	1.38	1.30	0.94	0.62
Follow-on	8.08	7.35	0.91	0.11	4.02	3.68	0.92	0.46
Initial	1.52	1.38	0.91	0.09	0.98	0.87	0.89	0.30
Cap. Structure	**1.77**	**1.61**	**0.91**	**0.10**	**1.51**	**1.33**	**0.88**	**0.26**
Leverage Effect	1.67	1.50	0.90	0.06	1.43	1.25	0.87	0.24
Tax Shield	2.47	2.34	0.95	0.37	1.11	0.89	0.80	0.06
Interest	2.44	2.31	0.95	0.35	1.10	0.89	0.81	0.07
Δ Baseline	**1.40**	**1.27**	**0.91**	**0.10**	**1.28**	**1.04**	**0.81**	**0.07**
Cash Flow	**1.82**	**1.68**	**0.92**	**0.17**	**1.52**	**1.31**	**0.86**	**0.21**
Acq. Finance	3.32	2.63	0.79	0.00	1.44	1.32	0.92	0.49
Alpha	1.87	1.74	0.93	0.23	1.50	1.34	0.89	0.32
Industry	1.47	1.36	0.93	0.21	1.42	1.30	0.92	0.48
Δ Multiple	**1.78**	**1.56**	**0.88**	**0.02**	**1.78**	**1.34**	**0.75**	**0.02**
Organic	1.60	1.43	0.90	0.06	1.50	1.19	0.79	0.05
Inorganic	3.59	3.20	0.89	0.05	1.65	1.61	0.98	0.84
Acquired	3.23	2.90	0.90	0.06	1.50	1.46	0.97	0.80
Industry	1.67	1.53	0.92	0.13	1.98	1.84	0.93	0.53
Δ Margin	**2.27**	**2.17**	**0.96**	**0.46**	**2.06**	**1.98**	**0.96**	**0.72**
Alpha	2.38	2.27	0.95	0.41	2.04	1.88	0.92	0.48
Acquired	3.18	3.07	0.97	0.56	1.61	1.55	0.97	0.77
Industry	2.04	1.96	0.96	0.53	2.34	2.31	0.99	0.90
Δ Revenue	**1.67**	**1.55**	**0.93**	**0.21**	**1.08**	**1.00**	**0.92**	**0.50**
Alpha	1.99	1.89	0.95	0.40	2.10	1.92	0.92	0.46
Acquired	3.19	2.52	0.79	0.00	1.35	1.27	0.94	0.57
Industry	1.48	1.40	0.94	0.31	1.65	1.62	0.98	0.88

The coefficients of variation (CV) have been calculated by dividing standard deviation with the mean of a driver's absolute values to get comparable variations across different drivers. Total columns illustrate the CV of each driver across all transactions of full and add-on samples. GP fixed columns illustrate CV after controlling for GP fixed effect. Ratios compare the CV values before and after controlling GP fixed effect, and thus the lower the ratio, the more a driver's CV is explained by GP. F-test measures the two-tailed probability that differences in standard deviations are not significantly different.

In both samples and for all value creation drivers, the ratios between CVs before and after controlling for GP fixed effect are below one, indicating that variations within GPs are smaller than variation in all transactions. For total return, the corresponding ratio was 0.93 in full sample and 0.91 in add-on sample, with considerably high F-test values of 0.19 and 0.40. Thus, while the CV values of total return are low, the relative share of GP fixed effect of total variation seems to be significantly larger in some other drivers, indicating a higher dependency on GP selection. For capital structure effect, the ratio between total and GP-fixed CV is 0.91 for full sample and 0.88 in add-on sample, indicating that GPs' ability to utilize higher leverage than market on average is slightly more dependent on GP than change in the total investment value. F-test values of 0.10 and 0.26 are also significantly lower than corresponding values for change in investment value indicating better reliability of the results. The variation in the total effect of incremental leverage seems to be even more dependent on GP. Similarly, lower ratios and lower F-test values of baseline return indicate that industry leverage adjusted return might better explain the skill of GPs.

GPs' ability to create value through the generation of cash flow also seems to be slightly more dependent on GP than total return. In full sample, the ratio was 0.92 and F-test value 0.17, indicating a little more dependency on GP than in total return. In add-on sample, GPs seem to explain more of the variation with a ratio of 0.86 and F-test value of 0.21. With higher ratios, the sub-drivers of cash flow seem to be less persistent than the total effect, and no individual sub-driver seems to explain the persistence.

Value creation through multiple growth seems to be the most GP-dependent driver in our samples. The ratios are 0.88 in full-sample and 0.75 in add-on sample, while F-test value of 0.02 implies high reliability of the result. Thus, variations in the contributions of multiple growth are significantly higher within all transactions than within the transactions of GPs. A significant amount of the variation occurs due to the differences in the average multiple growth contributions of a GP. The organic multiple growth driver also implies persistence, although lower than in total multiple growth change. However, the persistence of multiple growth seems to be driven by organic multiple driver, indicating a persistent value creation skill. It could be argued that GPs aim to grow multiple despite the strategy of the deal – unlike some other drivers that might be more dependent on deal strategy – and therefore a greater share of the variation in multiple contributions is explained by GP.

In addition to the low relative persistence of the margin effect, the variation seems to be very little dependent on GP. In both samples, the ratio was 0.96 and F-test values were high. Alpha margin driver seems to be a little more GP-dependent driver with slightly lower ratios of 0.95 and 0.92. The result indicates that little difference exists among the expected variance of GPs' margin contribution.

The share of the GP fixed effect in the variation of value creation through revenue growth is close to the ratio of total return. In full sample the ratio was 0.93 with an F-test value of 0.21. In add-on sample, the average persistence was significantly higher but still GP fixed effect explained only little of the variation, resulting in a ratio of 0.92 with an F-test value of 0.50. In the sub-categories of revenue growth, all drivers implied slightly weaker dependency on GP.

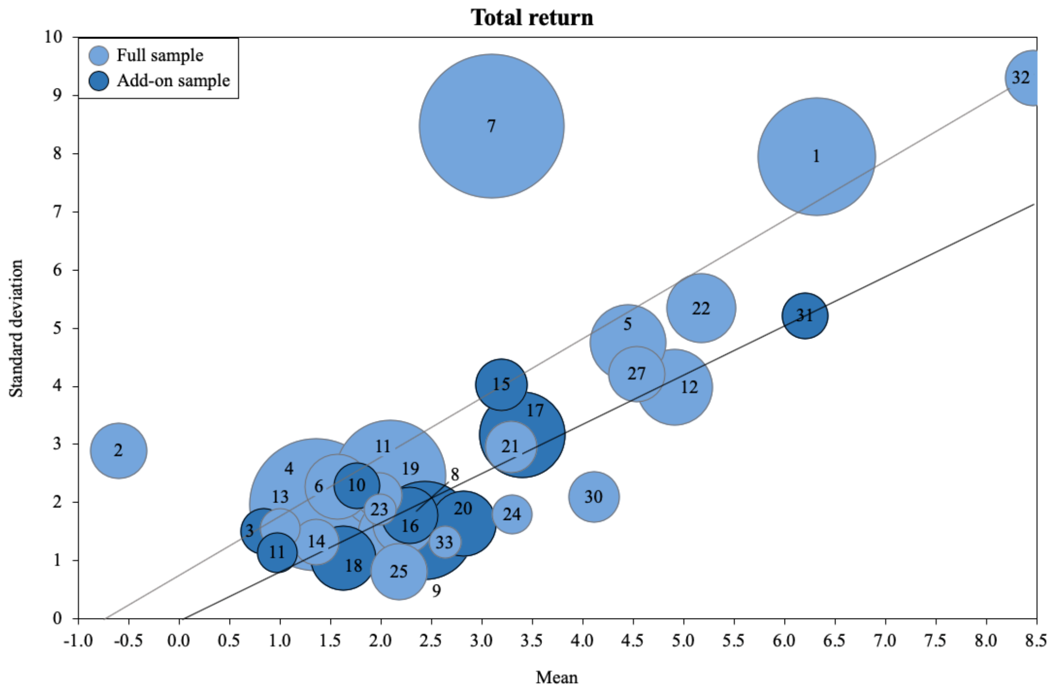
The results of table 12 illustrate the average variation in drivers' contribution as well as GPs' average dependency on variation. While it gives an idea of the average persistence of value creation drivers, it does not reveal the differences between GPs' value creation skills. Furthermore, the low ratios of some drivers indicate that the averages between GPs are significant, and thus LPs should pay attention to selecting GPs with a high expected value and low variation (high persistence). Thus, in addition to considering the variation within a GP in a specific driver, one should consider the GP's average value creation contribution when assessing the significance of a value creation driver.

4.2.3 Mean contribution and volatility

The relative importance of a driver and its relevance as a predictive return indicator can be seen as a function of expected average return and volatility. In general, risk-averse LP would prefer a GP that can generate high returns with low volatility. The risk appetite of an LP defines how much volatility it can withstand at a given level of expected return. Similarly, the higher the average contribution and the lower the volatility, the more attractive an individual value creation driver is. Next, we will examine the relation between average contribution and standard deviation of various levers of alpha across GPs. To anonymize the results, random numbers from 1 to 35 has been set to represent each GP in our samples.

Total return

Figure 16 illustrates the mean and standard deviation of total return by GP. The graph illustrates how the higher return is positively associated with standard deviation on average. For example, GP number 30 has created significantly higher average returns than GP number 6 while the volatilities of the returns are roughly equal. Thus, GP number 30 seems a more attractive investment target than GP number 6 in terms of risk and expected return. In general, GPs below trendlines have exhibited high return when compared to the standard deviation of the results and seem most attractive investment targets based on historical returns. Attractive GPs include for example numbers 12, 25 and 30 in full sample, and numbers 9 and 20 in add-on sample. On the other hand, risk-averse LP might want to avoid GPs generating low returns with high volatility. These GPs include numbers 2 and 7 in full sample, and numbers 3 and 10 in add-on sample.

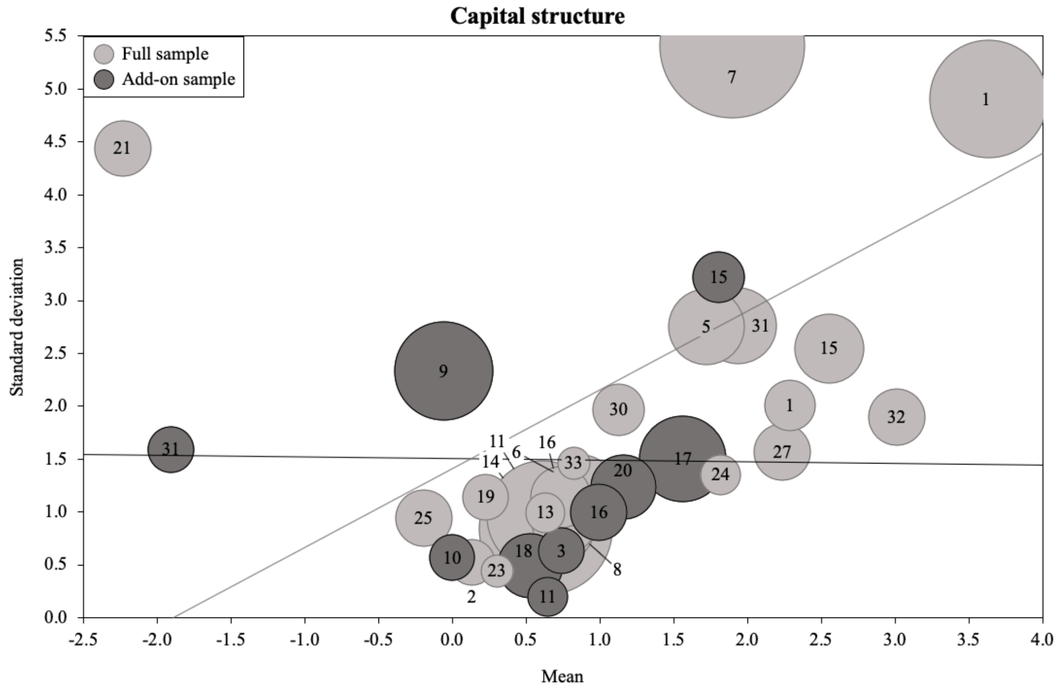


Each bubble illustrates the average value creation of an anonymous GP. Bubble area illustrates the number of transactions by the given GP. Grey (full sample) and black (add-on sample) trendlines represent the average relation between average and standard deviation.

Figure 16 Mean and standard deviation of total return by GP

Capital structure

Closer examination of alpha drivers reveals whether specific GPs have the skill to create consistently industry outperforming returns with low volatility with a specific value creation driver. First, figure 17 represents the value creation through capital structure effect by GP, which describes the net effect of GPs' ability to exploit higher leverage than industry peers on average. While previously introduced results highlight the relatively high contribution of incremental leverage in value creation and the relatively high average persistence when compared to some other drivers, figure 14 reveals how significant differences appear between GPs when it comes to exploiting high leverage in value creation.



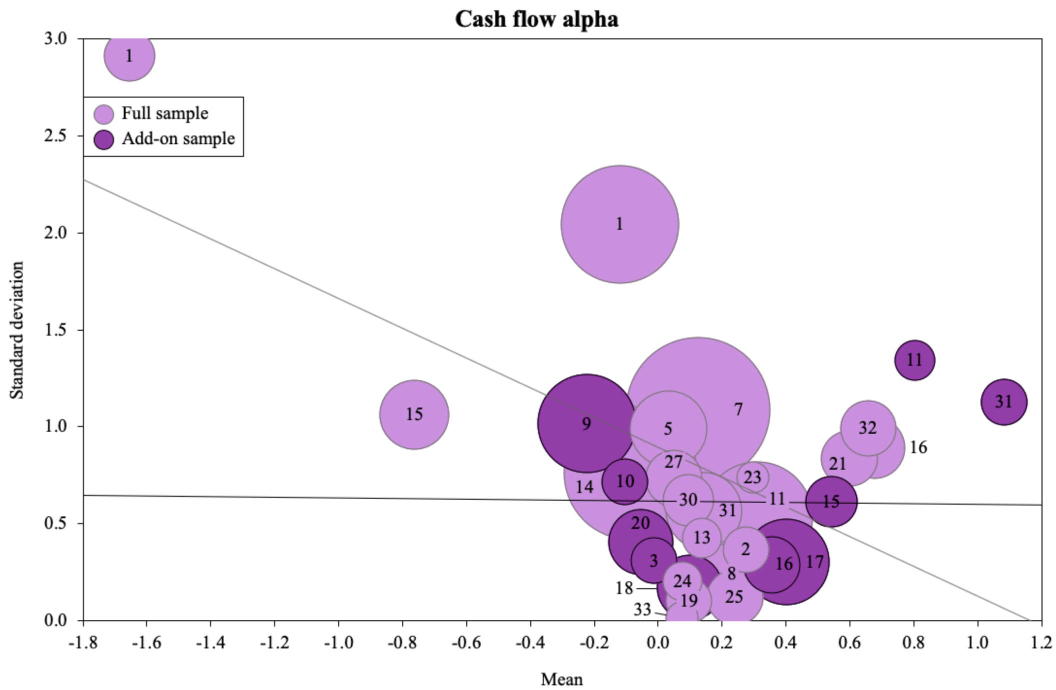
Each bubble illustrates the average value creation of an anonymous GP. Bubble area illustrates the number of transactions by the given GP. Grey (full sample) and black (add-on sample) trendlines represent the average relation between average and standard deviation.

Figure 17 Mean contribution and standard deviation of capital structure effect by GP

While some GPs seem to have lower leverage than industry on average (especially GPs 21 and 31), others have captured significant returns with relatively high persistence. For example, GPs 27 and 32 in full sample have been able to generate TMs of 2.24 and 3.01 with relatively small standard deviations of 1.57 and 1.90, respectively. The result indicates that these GPs have constant access to higher leverage than average industry peers, and they are able to turn leverage into value with significantly higher persistence than most other GPs. On the other hand, GP number 7 has also above average contribution with incremental leverage, but the high volatility indicates inconsistent ability to create value, which might be partly explained by investments ending up to bankruptcy.

Cash flow alpha

While the average contribution of cash flow alpha was only between 0.08 and 0.18 and the relative persistence seemed moderate, significant differences in persistence occurred between GPs, especially in add-on sample. Figure 15 represent the mean contributions and standard deviations of cash flow alpha driver by GP. When it comes to generating more cash flow than industry peers on average, the correlation between average contribution and standard deviation seems low compared to the apparent positive association in other drivers.



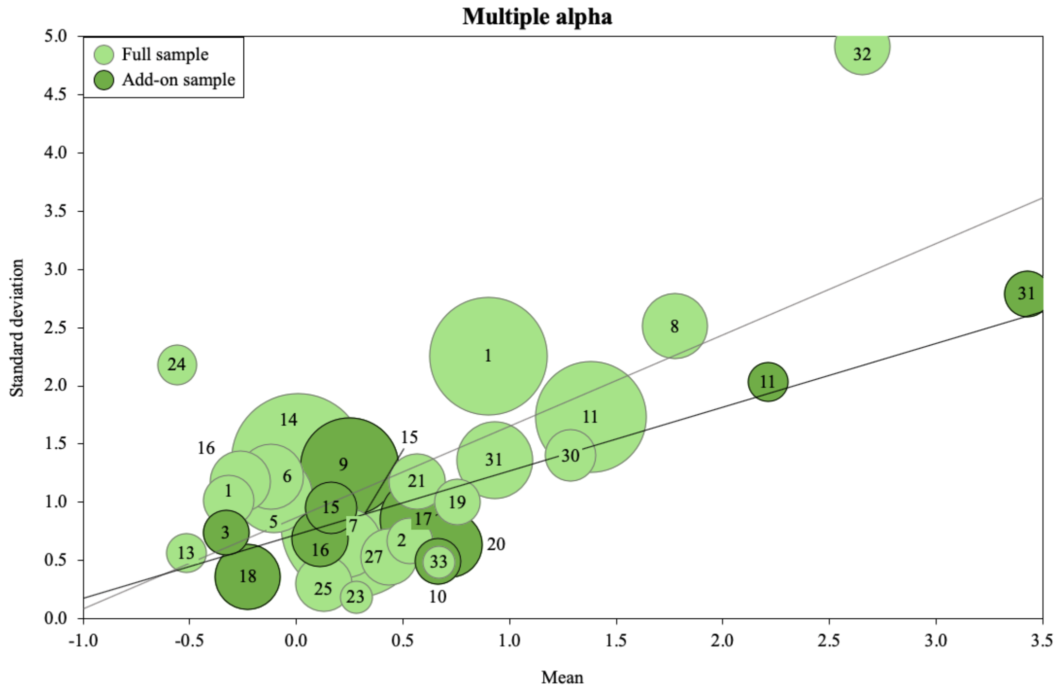
Each bubble illustrates the average value creation of an anonymous GP. Bubble area illustrates the number of transactions by the given GP. Grey (full sample) and black (add-on sample) trendlines represent the average relation between average and standard deviation.

Figure 18 Mean contribution and standard deviation of cash flow alpha by GP

The results of figure 18 indicate that some GPs are able to generate value by higher cash flow than industry average and maintain a significantly higher ratio of mean contribution and standard deviation than other GPs on average. For example, in add-on sample, GPs number 16 and 17 have yielded positive value with incremental cash flow while GPs 9 and 10 have had a negative contribution on average with significantly lower persistence. The result indicates that although the average contribution of cash flow alpha is relatively small, significant differences appear in the differences between GPs to create value and thus such GPs exist that can create value more and with higher persistence than average. Furthermore, by avoiding worst performing and low persistence GPs, such as GPs number 21 and 22, LPs might yield above-average FCF returns in the future.

Multiple alpha

In previous results, we demonstrated multiple growth to be the most significant contributor to baseline return, while organic alpha represented the majority of the alpha multiple growth. Furthermore, despite the moderate persistence compared to other drivers, the variation was found to be highly dependent on GP, indicating high differences in the averages between GPs. Figure 19 demonstrates how the mean contributions of organic multiple alpha driver ranged from negative values to contributions of over 3 TM.



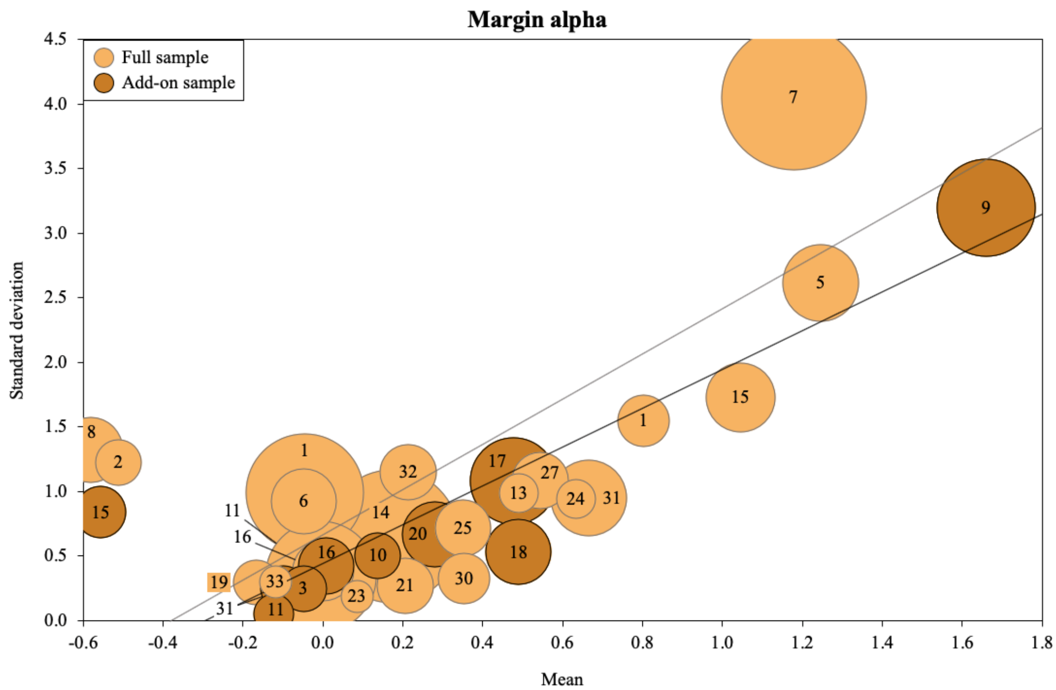
Each bubble illustrates the average value creation of an anonymous GP. Bubble area illustrates the number of transactions by the given GP. Grey (full sample) and black (add-on sample) trendlines represent the average relation between average and standard deviation.

Figure 19 Mean contribution and standard deviation of multiple alpha by GP

Despite the positive association between mean contribution and standard deviation, some GPs demonstrated a skill of growing multiple with relatively low standard deviation. For example, GP number 20 demonstrated more persistent organic multiple growth than GP number 3, while the mean contribution remained significantly higher. Similarly,a in full sample, GP number 30 yielded an average TM of 1.29 by growing multiple faster than industry peers, while GP number 16 yielded a negative TM of -0.26 with only little higher persistence.

Margin alpha

According to previously introduced results, the average contribution of margin growth was between 0.45 and 0.48. The contribution of alpha margin was even greater, suggesting a small negative margin change in industry peers on average. However, the persistence turned out to be low and only little of the high volatility was explained by GP. Figure 20 illustrates the positive correlation between standard deviation and mean contribution of margin alpha driver by GP. With the exception of a few outliers – GPs 8, 14, 15 and 7 – no GP seem to stand out in terms of an exceptionally low ratio of mean contribution and standard deviation. Even for the GPs yielding highest ratios of mean contribution and standard deviation – such as GPs number 18 and 30 – the ratio remains low compared to other drivers. This might indicate that despite the majority of margin contribution was allocated to alpha, alpha might be captured through indirect effects, such as exploiting economies of scale and realizing synergies from add-on acquisitions rather than cost-cutting of a GP.

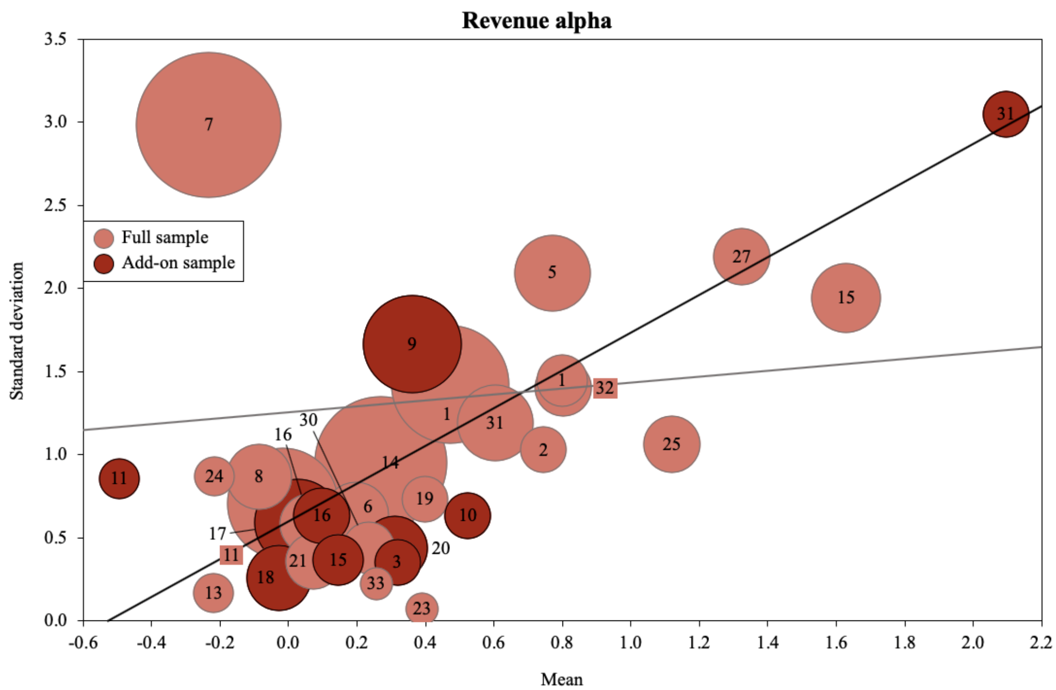


Each bubble illustrates the average value creation of an anonymous GP. Bubble area illustrates the number of transactions by the given GP. Grey (full sample) and black (add-on sample) trendlines represent the average relation between average and standard deviation.

Figure 20 Mean contribution and standard deviation of margin alpha by GP

Revenue alpha

Previous results demonstrate the importance of revenue growth in value creation but indicate that only little of it is actually captured as alpha of a GP. However, when compared to other drivers, total revenue growth seems to be the most persistent of five main drivers while revenue alpha seems less persistent. Furthermore, GPs seemed to explain only little of the variation. The results of figure 21 demonstrate a positive correlation between mean contribution and standard deviation. A significant outlier in the sample is GP number 7, whose average contribution is negative with remarkably low persistence. The result shows how different the value creation strategy of GP number 7 has been from the other GPs, who in turn yielded significantly higher returns by growing margin (see figure 20).



Each bubble illustrates the average value creation of an anonymous GP. Bubble area illustrates the number of transactions by the given GP. Grey (full sample) and black (add-on sample) trendlines represent the average relation between average and standard deviation.

Figure 21 Mean contribution and standard deviation of revenue alpha by GP

The results suggest that some GPs have demonstrated highly persistent value creation through alpha revenue growth. For example, GP number 25 has yielded mean contribution of 1.12 with a standard deviation of 1.06. Furthermore, for example, GP number 10 yielded significantly higher returns than GP number 9 with significantly higher persistence. Thus, the results indicate that organic growth of revenue can also be a relatively persistent driver.

The results of this chapter have demonstrated that while the coefficient of variation was higher for individual value creation drivers than for total return, the examination of the mean contribution and standard deviation between different value creation drivers and GPs reveal significant differences in value creation. Some GPs are able to create higher mean returns with a specific driver than others while maintaining relatively high persistence. Furthermore, in addition to individual drivers, the inspection of the graphs represented in this chapter reveals the different patterns of value creation across GPs.

For example, 99% ((1.18+1.90)/3.10) of the value creation of GP number 7 was attributable to alpha margin growth and capital structure leaving a very little contribution to other drivers. On the other hand, GP number 9 executed numerous add-on acquisitions and realized majority of value through revenue growth and alpha margin growth, most of which was likely captured as cost synergies. However, the average industry leverage of GP number 9 resulted in a lower total return than GP number 7, but with significantly higher persistence.

5. Discussion and conclusions

5.1 Discussion of the results

The purpose of this study was to improve understanding of value creation in PE as well as to examine the skills of GPs to create persistent value with particular value creation drivers. A large deal-level dataset of PE transactions executed between 1990 and 2015 was used to examine value creation attribution. To quantify the contributions of various sources and causes of value creation, we were the first to apply the IVC 2.0 framework with a large deal-level dataset. Especially, we contributed to the research on PE value creation in small- and mid-cap transactions in Europe. Full sample (*n*=297) and add-on sample (*n*=75) was used to exploit both large and more accurate datasets.

5.1.1 Value creation

The results indicate that GPs' ability to use higher leverage than the market on average represents the greatest individual driver of value creation and the largest contributor to public market outperformance. The contributions were 40% and 24% in the two samples, which are in line with most previous studies suggesting that incremental leverage represents around a third of value creation (Achleitner et al. 2011, Kaserer 2011, Puche et al. 2015, Ernst & Young 2014). However, due to methodological differences, our results are not fully comparable with previous studies.

For industry leverage adjusted return, valuation multiple growth is the most significant driver and largest individual driver explaining public market outperformance. The contribution of multiple growth was 22% and 31% in the two samples, while add-ons acquired by a lower multiple than portfolio company caused an additional contribution of -3% in add-on sample. The findings thus suggest a more significant role for multiple expansion in value creation than the previous studies, which have found smaller and highly varying results ranging from contributions of -10 to 20% (Guo et al. 2011, Kaserer 2011, Puche et al. 2015). Furthermore, according to our results, roughly a third of organic multiple expansion is achieved by exploiting multiple arbitrage resulting from the integration of add-on targets as part of the portfolio company's platform. The significant contribution of organic multiple growth indicates that GPs are either able to negotiate lower entry prices or higher exit prices than industry peers. Higher exit multiples can also be a result of selecting the most potential exit route at each economic situation, such as a sell to a strategic buyer (Gompers et al. 2016). As a consequence of increasing company sizes on average, organic multiple growth is also likely to be an indirect consequence of revenue growth – both organic and inorganic – which is found to be positively correlated to exit multiple (Achleitner et al. 2011).

Previous studies have highlighted the increasingly important role of operational improvements in value creation and found total contributions of operational improvements to range from 50 to 75% (Kaserer 2011, Graf et al. 2012, Gompers et al. 2016, Puche et al. 2015). In our samples, operational improvements averaged a significant contribution of 37 to 45%, which, however, was considerably lower than previous studies have demonstrated.

Within operational improvement drivers, organic revenue growth represented the most important driver with a contribution of around 20% in both samples, which is significantly lower than 30 to 40% suggested by previous studies (Kaserer 2011, Puche et al. 2015). However, the acquired revenue contribution of 18% in add-on sample raised the total contribution of revenue growth to the level of previous findings. Since around a half of revenue growth is actually acquired on average, the role of organic revenue growth seems significantly smaller than previous studies suggest. Furthermore, since GPs acquire targets from growing industries on average, only 28% of total revenue growth contribution is allocated to alpha, and thus the role of revenue growth seems to be relatively small when it comes to outperformance over public market peers. Our results are supported by the findings of Söffge and Braun (2018) who find revenue growth to be a significant driver only in organic deals, which represented roughly a third of our add-on sample.

While previous studies have suggested that GPs rather focus on revenue growth than margin improvement, our results suggest a roughly equal contribution to value creation. We found margin effect to have average contributions of 14% and 18%, while the corresponding contribution ranged from 7 to 17% in the studies of Kaserer (2011) and Puche et al. (2015). Furthermore, since industry margin improvements were negative on average, the contributions of margin alpha were 20% of total value creation, representing a significantly higher role in outperforming value generation than revenue growth. Although add-on targets did not improve the profitability of platforms at the time of acquisitions on average, it is likely that significant part of alpha margin was captured through economies of scale and realization of synergies resulting from add-on acquisitions during holding periods.

In our results, the role of FCF in value creation was significantly lower than in previous studies. While Kaserer (2011) found an average contribution of 27% and Puche et al. (2015) a contribution of 12%, the average contributions in our samples were only 3% and 8%. Similarly, when it comes to creating alpha performance, the contribution was only 7% in add-on sample, representing a considerably minor role in outperformance. However, to some extent, the differences between our results and previous studies are explained by the lack of dividend information in our data. Thus, our results are less reliable when it comes to the generation of FCF during the holding period.

Although alpha captures the GPs' outperformance over public peers in various value creation levers, it cannot be seen only as a skill of GPs to create value. GPs are likely to acquire companies with above-average past performance, which can be expected to result in outperformance during holding period without the contribution of GP on average. Therefore, in addition to GPs' abilities to improve the operational performance of portfolio companies, alpha can be seen as GPs' ability to select targets that outperform peers both in the past and likely also during PE ownership. Similarly, industry drivers can be seen both as industry benchmark returns and as GPs' ability to select growing industries.

5.1.2 Persistence

In addition to studying the contributions of various value creation drivers, we were the first to study the persistence of value creation sources and causes. We found total return and industry leverage adjusted baseline return to be the most persistent drivers of value creation when using the coefficient of variation (CV) as the measure of persistence. However, the volatilities of total returns in the two samples were little dependent on GPs' fixed effect, while more significant differences between GPs were found in some other drivers of value creation.

In addition to the significant contribution to value creation, GPs' ability to exploit higher leverage than industry peers represented one of the most persistent drivers on average. Especially for some individual GPs, incremental leverage yielded more persistent value than total return, representing a persistent source of value. Our results thus suggest that the ability to inflate returns with high leverage can be a persistent source of value for certain GPs, which LPs should consider as a GPs' potential to create value also in the future.

Multiple expansion represented roughly as persistent value creation as leverage effect on average, but it was significantly more dependent on GP. We found that a significant part of the volatility in multiple driver was explained by the differences between GPs rather than volatile contributions within GPs. Furthermore, multiple persistence was found to be driven by organic multiple growth which indicates that persistence is not driven by different market conditions between GPs or multiple arbitrage resulting from add-ons. Thus, the results indicate that certain GPs have a persistent skill to negotiate lower entry multiples or higher exit multiples than others. However, since significant differences exist between GPs, LPs should pay attention to selecting GPs that have demonstrated consistent multiple growth in the past.

Despite the relatively low contribution of alpha revenue growth in value creation, total revenue growth driver represented the most persistent value creation in our results. However, the sub-drivers of revenue growth indicate that persistence yields from acquired growth and growing industry rather than alpha. Furthermore, little of the volatilities in revenue drivers is explained by the differences between GPs. Our results thus indicate that GPs' role in organic revenue growth seems to be small and only a few GPs seem to stand out in terms of a skill to grow revenue organically.

While margin growth – and especially alpha margin – represented a significant role in value creation, margin growth seems to be the least persistent value creation driver. In addition to the low persistence, very little of the high variation seemed to be explained by GP. The results indicate that GPs' ability to improve profitability, exploit economies of scale and realize synergies create significant value on average, but the value creation is highly volatile. Thus, although a GP would have demonstrated margin growth in the past, it might still be a poor indicator of future profitability improvements.

The generation of FCF represented a small role in value creation, but it seems to be a reasonably persistent value creation driver. Persistence was driven by alpha FCF driver and GPs explained some of the variations, indicating that some GPs can create more persistent value than others. However, the lack of dividend information prevents us from making solid conclusions about the persistence of FCF generation.

Since GPs are likely to exploit various strategies in the case of different portfolio companies, some of the low persistence can be explained by the divergent value creation focuses of a GP's transactions. For example, a GP could focus on rapid growth in one transaction, while in other the focus can be in profitability improvements. This could also explain why our results found total return to be more persistent than the individual drivers. On the other hand, one could argue that GPs aim to maximize multiple growth despite the deal strategy, which might explain the higher persistence of that driver.

Although our results focused on the average contribution and persistence of different value creation drivers, significant differences exist between both value creation patterns and persistence of different GPs. For example, some GPs exploited consistently high leverage to inflate equity returns, while others used little leverage and focused on value creation through operational improvements during the holding period. Others, in turn, demonstrated a highly persistent skill of acquiring companies as a part of platforms and creating value through profitability improvements and multiple growth. Therefore, we suggest that LPs should examine the past value creation and persistence of potential GPs parallel with the qualitative analysis of GP's investment strategy to evaluate the GP's ability to create value in the future.

5.2 Limitations

This thesis focused on mid- and large-cap buyout deals in European region between years 1990 and 2015. Thus, our samples offer a view of the value creation and persistence of a relatively small deal sample during that period. Although most of our results have not been studied at the level of detail we offered, the differences to comparable results in previous literature can be explained to some extent with the focus of our sample. For example, the higher bankruptcy risk of smaller companies may lead to higher multiple growth and lower leverage effect than suggested by previous research.

Perhaps the most severe limitations of this study relate to the quality of data. The transaction data was originally collected from fund managers, and thus individual managers might have different entry practices when it comes to for example exchange rates and acquired values. The most severe shortcoming of the data was the lack of dividend information, which can be a significant source of value. This effected especially to the results of value creation and persistence of cash flow.

Furthermore, some assumptions had to made due to missing data. In transaction values, we assumed that net debt equals debt to get leverage ratio values at entry. Interest and tax rates were also collected from external sources using company headquarters and time as the criteria. The actual contribution of incremental debt and tax shield could thus be significantly different from our results in practice, and this is also why they had a small focus in this thesis.

5.3 Suggestions for future research

Despite the highly informative results of the IVC 2.0 framework, the manner in which intrinsic and extrinsic value creation are separated could be enhanced. The components of alpha can be seen as a GP's skill to select outperforming targets, an indirect effect of add-on acquisitions and actual contribution of the portfolio company and GP to value creation. Thus, it can not be seen only as the contribution of GP, which blurs the view of GPs value creation to some extent. However, more detailed data is needed to better separate the intrinsic and extrinsic causes of value creation as suggested by Berg and Gottschalg (2005).

Competition has been found to be a significant performance driver in the PE sector (Braun et al. 2017b), but we did not examine the results based on competitive situation or timing. Since performance persistence has vanished to some extent as the consequence of increased competition, future scholars could examine how the relative contribution and persistence of value creation drivers vary in different competitive situations and throughout time. While this thesis focused on the persistence of alpha drivers, it would also be interesting to study the persistence of industry drivers to capture whether specific GP's are able to consistently select value-creating industries. Furthermore, since GPs' varying value creation strategies might explain some of the low persistence in our results, it would be interesting to group transactions based on deal strategy and examine the value creation patterns and returns of various strategies as well as the ability of specific GPs to execute these strategies successfully.

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